Supporting Material for "Current Research Overstates American Support for Political Violence"

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S1 Context

S1.1 Engagement with Current Estimates

S1.1.1 Google Scholar

We searched for citations to Kalmoe, Nathan P and Lilliana Mason. 2019. Lethal mass partisanship: Prevalence, correlates, and electoralcontingencies. In *NCAPSA American Politics Meeting*.

S1.1.2 News Coverage

To count news coverage we used a basic search on Lexis Nexis:

Language: English
Terms: "Kalmoe" and "Mason"

We also used the same search terms on Google News.

The resulting articles were then manually cleaned to remove duplicates and unrelated articles.

S1.1.3 Social Media

Twitter
We used the Twitter Academic API to obtain all tweets with a link to an article on Kalmoe and Mason results. We then summed likes, quotes, retweets and total tweets. NOTE: This is a dramatic under-count of engagement as it does not count exposure to these tweets or the number of users who clicked on the links.

URLs:

```
https://www.nytimes.com/2019/03/13/opinion/hate-politics.html
www.politico.com/news/magazine/2020/10/01/political-violence-424157
https://politi.co/3cJtVHQ
https://politi.co/2SeWmnv
https://www.dannyhayes.org/uploads/6/9/8/5/69858539/kalmoe___mason_ncapsa_2019_-_lethal_partisanship_-
_final_lmedit.pdf
https://www.washingtonpost.com/politics/2021/01/11/what-you-need-know-about-how-many-americans-
condone-political-violence-why/
https://fivethirtyeight.com/features/our-radicalized-republic/
https://www.vox.com/policy-and-politics/22217576/trump-insurrection-capitol-america-political-
violence
https://www.nbcnews.com/think/opinion/pro-trump-capitol-riot-violence-underscores-bipartisan-
danger-dehumanizing-language-ncna1254530
https://www.opendemocracy.net/en/age-trump-over-now-us-must-tackle-its-polarisation/
https://www.washingtonpost.com/opinions/2019/10/04/short-primer-preventing-political-violence/
https://theweek.com/articles/941014/political-violence-coming-from-direction-country-far-
right
https://www.oregonlive.com/politics/2019/04/downright-evil-americans-increasingly-believe-
those-in-opposing-political-party-behave-like-animals-study.html
https://www.theguardian.com/us-news/2021/jul/19/joe-biden-republicans-polarization-us-politics-
texas
https://www.newyorker.com/magazine/2021/07/26/are-americans-more-trusting-than-they-seem
https://www.latimes.com/opinion/story/2020-09-17/americans-anti-democratic-sentiment-bartels
https://www.governing.com/now/violence-is-likely-to-escalate-ahead-of-the-election.html
https://carnegieendowment.org/2019/10/04/short-primer-on-preventing-political-violence-pub-
79997
```

https://www.washingtonpost.com/politics/fear-of-election-violence/2020/10/30/5b4f5314-17a3-11eb-befb-8864259bd2d8_story.html
https://www.nytimes.com/2021/01/18/us/supporters-of-donald-trump.html
https://lasvegassun.com/news/2020/sep/21/too-many-people-have-lost-faith-in-democracy/
https://www.washingtonpost.com/opinions/americans-are-at-each-others-throats-heres-one-way-out/2019/12/20/c8de01ca-2292-11ea-a153-dce4b94e4249_story.html
https://www.timesrecordnews.com/story/life/2021/01/16/mattingly-christians-and-conspiracies-dont-mix/6654273002/
https://www.vox.com/mischiefs-of-faction/2017/6/15/15808558/political-violence-eroding-democracy
https://www.tennessean.com/story/opinion/2020/02/17/science-gives-us-recipe-civil-conversations/4470881002/
https://www.newyorker.com/magazine/2020/11/16/pulling-our-politics-back-from-the-brink
https://www.knoxnews.com/story/entertainment/columnists/terry-mattingly/2021/01/14/doesnt-help-when-believers-join-americas-online-mobs-terry-mattingly/6630763002/
https://www.newyorker.com/news/daily-comment/is-american-tolerance-for-political-violence-on-the-rise
https://www.niskanencenter.org/the-role-of-political-science-in-american-life-science-of-politics-episode-100/
https://www.politico.com/magazine/story/2018/10/30/yes-political-rhetoric-can-incite-violence-222019
https://www.economist.com/briefing/2020/10/29/president-trump-has-had-real-achievements-and-a-baleful-effect
https://newrepublic.com/article/156402/hate-ballot
https://www.wsj.com/articles/crises-lay-bare-a-goodwill-deficit-in-america-11591623044
https://www.washingtonpost.com/politics/2019/12/02/both-democrats-republicans-were-once-white-majority-parties-now-race-divides-them/
https://fivethirtyeight.com/live-blog/biden-inauguration/
https://www.niskanencenter.org/the-niskanen-centers-science-of-politics-podcast/
https://www.csmonitor.com/USA/Politics/2017/0619/Is-America-s-political-atmosphere-dangerously-hot
https://www.usatoday.com/story/opinion/2019/04/12/record-breaking-national-deficit-partisanship-threaten-us-future-leadership-column/3438887002/
https://reason.com/2020/08/05/the-looming-illegitimate-election-of-2020/
https://reason.com/2019/10/01/in-todays-america-everybody-who-disagrees-with-you-is-a-traitor/

S1.2 Political Violence News Coverage

S1.2.1 Print/Online

To count print and online news coverage we used a basic search on Lexis Nexis:

Language: English
Period: 1/1/2016 - 8/31/2021
Terms: "political violence" and ("Democrat" or "Republican")

The resulting articles were then manually cleaned to remove duplicates and non-news sources.

This is a simplistic search, yet it establishes a conservative baseline of coverage of American political violence.

We plot results by Month and Year.

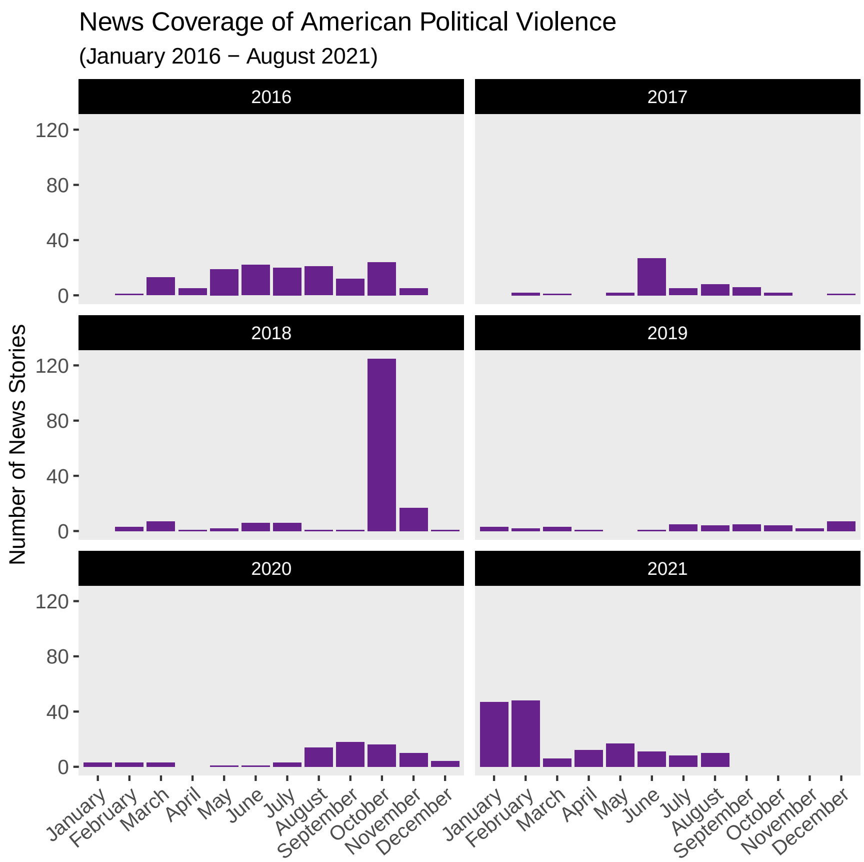

Figure S1: This plot shows counts of news coverage of American political violence by Month and Year.

S1.2.2 TV News

To count television engagement we used the same query and the Internet Archive's television news archive (see Figure S1).

S1.2.3 Twitter

To count Twitter engagement we counted references to January 6th, 2021. We did this to set a floor for discussion of political violence in America and because tweets lack the length and formal language of newspaper articles.

S2 Previously reported estimates

We conducted an exhaustive search of news articles reporting an estimate of public support for political violence. We recorded all aggregated estimates, and all estimates split by party. We first manually searched for estimates of support within the text using the following keywords: percent, per cent, %, "one in" (such as "one in three"), and "one-in". We then verified whether these were estimates of support for violence or other types of statistics (e.g., statistics such as "30% of Republicans say Democrats are evil" are not included). In particular, we identified which political violence survey question and wave from prior studies each estimate was based on. In a minority of cases, the survey question was clear but the survey wave was unclear. For instance, the estimate was from 2020, but we do not know if the estimate was derived from a September or October survey. We include these reported estimates despite the source ambiguity. On a few occasions, the reported support was given as a range (e.g., 15-20 percent). In each case, we converted this to the midpoint of the range (e.g., 18 for 15-20). Finally, we record each reported political violence support estimate within each story since some stories report multiple estimates of support for violence. These data are at the story-level.

S3 Study 1

S3.1 Sample Demographics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
age	1002	47.01	17.07	18	32	62	97
gender	1002						
... Female	520	52%					
... Male	482	48%					
race	1002						
... African American	132	13%					
... Asian	15	1%					
... Native American	16	2%					
... Other	57	6%					
... Pacific Islander	4	0%					
... White/Caucasian	778	78%					
pid	1002						
... Democrat	547	55%					
... Republican	455	45%					

Table S1: Summary Statistics for Study 1

S3.2 Treatment Text

S3.2.1 Oregon - Democratic Version

Suspect Drives Into Group of Republicans in Jacksonville

Republican volunteers in Jacksonville, Fla., were registering people to vote in a shopping center Saturday afternoon when a man drove a van through their red tent, then fled, according to law enforcement officials. The incident has drawn condemnation from prominent Florida lawmakers and President Trump.

Stan Gimm, 27, was charged with two counts of aggravated assault on a person 65 years old or older, plus criminal mischief and driving with a suspended license, jail records show.

A Spokeswoman said the statements made by Gimm "makes it clear that Saturday was a deliberate attack that was completely reprehensible and unacceptable."

S3.2.2 Oregon - Apolitical Version

Suspect Drives Into Group in Jacksonville

Volunteers in Jacksonville, Fla., were working in a shopping center Saturday afternoon when a man drove a van through their red tent, then fled, according to law enforcement officials. The incident has drawn condemnation from prominent Florida lawmakers and President Trump.

Stan Gimm, 27, was charged with two counts of aggravated assault on a person 65 years old or older, plus criminal mischief and driving with a suspended license, jail records show.

A Volunteer Spokeswoman said the statements made by Gimm "makes it clear that Saturday was a deliberate attack that was completely reprehensible and unacceptable."

S3.2.3 Florida - Republican Version

Republican Arrested After Assaulting Democratic Protesters

Republicans gathered in a Portland, Oregon suburb and formed a caravan and proceeded to assault Democratic protesters by pepper-spraying people and shooting paintballs. They also physically intimidated protesters by driving their trucks at unsafe speeds through crowded streets.

Thomas Kelly, a 31-year-old Portland Republican, was among the drivers arrested following the caravan. He was charged with Disorderly Conduct II and Interfering with a Peace Officer.

Portland Mayor Ted Wheeler, a Democrat, denounced the caravan. "All of us must take a stance against violence. It doesn't matter who you are or what your politics are. We have to all stop the violence," he said at a press conference.

S3.2.4 Florida - Apolitical Version

Man Arrested After Assaulting Pedestrians

A group gathered in a Portland, Oregon suburb and formed a caravan and proceeded to assault pedestrians by pepper-spraying people and shooting paintballs. They also physically intimidated people by driving their trucks at unsafe speeds through crowded streets.

Thomas Kelly, a 31-year-old Portland man was among the drivers arrested following the caravan. He was charged with Disorderly Conduct II and Interfering with a Peace Officer.

Portland Mayor Ted Wheeler denounced the caravan. “All of us must take a stance against violence. It doesn’t matter who you are, we have to all stop the violence,” he said at a press conference.

S3.3 Engagement Question

S3.3.1 Democratic Story

In what state did the event covered by the article you just read occur?

- Florida
- Nevada
- Georgia
- Alabama
- Texas
- South Carolina
- Kentucky

S3.3.2 Republican Story

In what state did the event covered by the article you just read occur?

- Oregon
- Nevada
- Washington
- California
- Idaho
- New Mexico
- Arizona

S3.4 Outcome Questions

Do you support or oppose the actions of [Stan Gimm/Thomas Kelly]?

- Strongly Support
- Support
- Neither support nor oppose
- Oppose
- Strongly Oppose

Was the driver justified or unjustified?

- Justified

- Unjustified

Should the driver face criminal charges?

- Yes
- No

S3.5 Heterogeneity by Copartisanship

While support for violence is low overall, we find that individuals are more willing to excuse the actions of co-partisans, which we present in Table S2. However, we find no consistent evidence that individuals are more permissive toward political violence than apolitical violence. Among those who were engaged in Study 1, we find that support for violence is higher when the assailant is from the same political party as the respondent. In Study 2, we find an increase in belief that the actions were justified, but the overall support is quite low. In Table S2, we present the coefficient estimates. Because nearly all respondents in Study 2 want to charge the assailant regardless of his party, the assailant's party has no discernible effect on support. This is consistent with prior work that shows partisan biases, especially with respect to deviations from democratic norms, are more about in-group love than out-group hate (1; 2).

Table S2: Respondents display a slight bias towards in-party assailants, though overall support is low.

	Study 1			Study 2		
	Justified	Support	Charged	Justified	Support	Charged
Out-party Suspect	−0.076	−0.246	0.075	−0.048	−0.231	0.007
	(0.037)	(0.144)	(0.029)	(0.017)	(0.052)	(0.007)
Intercept	0.157	2.139	0.892	0.068	1.401	0.989
	(0.025)	(0.099)	(0.020)	(0.012)	(0.037)	(0.005)
Observations	315	315	315	572	572	572

Likewise, we find almost no difference in support whether partisan information is provided. Consistently, respondents do not support the subject's actions, view the crime as unjustified, and want the assailant to be charged regardless of the information we provide. Where we find effects, they are relatively small and suggest that, at most, only a small share of the public supports political violence.

S3.6 Additional Results

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.98	3.06	0.19	0.44	0.92	0.76
	(0.08)	(0.15)	(0.02)	(0.06)	(0.02)	(0.05)
Apolitical Driver 2	0.70	−0.02	0.03	−0.00	−0.03	0.05
	(0.12)	(0.22)	(0.04)	(0.08)	(0.03)	(0.07)
Democrat Driver	0.73	0.15	0.00	−0.12	−0.05	0.08
	(0.12)	(0.20)	(0.04)	(0.08)	(0.03)	(0.06)
Republican Driver	0.16	0.05	0.05	−0.00	−0.03	−0.00
	(0.12)	(0.21)	(0.04)	(0.08)	(0.03)	(0.07)
Engaged Respondent		−1.48		−0.35		0.23
		(0.17)		(0.06)		(0.05)
Apolitical Driver 2 * Engaged Respondent		0.98		0.04		−0.11
		(0.26)		(0.09)		(0.07)
Democrat Driver * Engaged Respondent		0.69		0.14		−0.18
		(0.24)		(0.08)		(0.07)
Republican Driver * Engaged Respondent		0.03		0.05		−0.02
		(0.24)		(0.09)		(0.07)
Num. obs.	1002	1002	1002	1002	1002	1002

Table S3: Main outcome measures vs. the treatment condition and Engaged Respondent. The baseline category for the treatment is Apolitical Driver (Story 1). Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.98	2.23	0.19	0.26	0.92	0.93
	(0.08)	(0.12)	(0.02)	(0.04)	(0.02)	(0.02)
Apolitical Driver 2	0.70	0.50	0.03	−0.04	−0.03	−0.04
	(0.12)	(0.17)	(0.04)	(0.05)	(0.03)	(0.03)
Democrat Driver	0.73	0.45	0.00	−0.08	−0.05	−0.02
	(0.12)	(0.17)	(0.04)	(0.05)	(0.03)	(0.03)
Republican Driver	0.16	0.11	0.05	0.04	−0.03	−0.05
	(0.12)	(0.17)	(0.04)	(0.05)	(0.03)	(0.03)
Republican		−0.54		−0.16		−0.03
		(0.16)		(0.05)		(0.03)
Apolitical Driver 2 * Republican		0.42		0.14		0.03
		(0.24)		(0.07)		(0.05)
Democrat Driver * Republican		0.61		0.18		−0.07
		(0.23)		(0.07)		(0.06)
Republican Driver * Republican		0.10		0.01		0.04
		(0.23)		(0.07)		(0.05)
Num. obs.	1002	1002	1002	1002	1002	1002

Table S4: Main outcome measures vs. the treatment condition and party ID. The baseline category for the treatment is Apolitical Driver (Story 1). Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.33	0.27	0.91
	(0.15)	(0.04)	(0.03)
Apolitical Driver 2	0.45	−0.00	−0.04
	(0.21)	(0.06)	(0.04)
Democrat Driver	0.44	−0.07	−0.03
	(0.22)	(0.06)	(0.05)
Republican Driver	0.26	0.13	−0.04
	(0.21)	(0.07)	(0.04)
Weak Dem.	−0.67	−0.19	0.09
	(0.23)	(0.07)	(0.03)
Lean Dem.	0.07	0.23	0.09
	(0.44)	(0.17)	(0.03)
Lean Rep.	−0.93	−0.27	−0.11
	(0.39)	(0.04)	(0.18)
Weak Rep.	−0.81	−0.18	0.06
	(0.21)	(0.06)	(0.04)
Strong Rep.	−0.52	−0.17	−0.03
	(0.20)	(0.06)	(0.05)
Apolitical Driver 2 * Weak Dem.	0.58	0.04	−0.05
	(0.36)	(0.10)	(0.07)
Democrat Driver * Weak Dem.	0.38	0.14	0.03
	(0.35)	(0.11)	(0.05)
Republican Driver * Weak Dem.	−0.39	−0.17	0.01
	(0.32)	(0.09)	(0.06)
Apolitical Driver 2 * Lean Dem.	−0.49	−0.41	0.04
	(0.70)	(0.19)	(0.04)
Democrat Driver * Lean Dem.	−0.14	−0.33	−0.07
	(0.63)	(0.20)	(0.11)
Republican Driver * Lean Dem.	−0.66	−0.63	−0.10
	(0.58)	(0.17)	(0.14)
Apolitical Driver 2 * Lean Rep.	1.58	0.15	0.10
	(0.62)	(0.15)	(0.23)
Democrat Driver * Lean Rep.	1.02	0.07	−0.05
	(0.57)	(0.06)	(0.25)
Republican Driver * Lean Rep.	0.84	0.25	0.12
	(0.66)	(0.19)	(0.22)
Apolitical Driver 2 * Weak Rep.	0.58	0.00	0.01
	(0.33)	(0.09)	(0.06)
Democrat Driver * Weak Rep.	0.77	0.09	−0.06
	(0.35)	(0.10)	(0.08)
Republican Driver * Weak Rep.	−0.17	−0.20	−0.08
	(0.30)	(0.08)	(0.08)
Apolitical Driver 2 * Strong Rep.	0.30	0.18	0.02
	(0.31)	(0.09)	(0.07)
Democrat Driver * Strong Rep.	0.46	0.21	−0.04
	(0.30)	(0.09)	(0.08)
Republican Driver * Strong Rep.	−0.05	−0.03	0.10
	(0.31)	(0.09)	(0.07)
Num. obs.	998	998	998

Table S5: Main outcome measures vs. the treatment condition and 7-point party ID. The baseline category for the treatment is Apolitical Driver (Story 1), and the baseline category for 7-point party ID is Strong Democrat. Coefficients are from an ordinary least squares regression with HC1 standard errors. We note that this analysis was not pre-registered.

	Support	Justifed	Charged
(Intercept)	2.33	0.20	0.91
	(0.06)	(0.02)	(0.01)
In-Party Driver	0.19	0.05	−0.05
	(0.11)	(0.03)	(0.03)
Out-Party Driver	−0.02	−0.03	0.00
	(0.11)	(0.03)	(0.02)
Num. obs.	1002	1002	1002

Table S6: Main outcome measures vs. the treatment condition. The baseline category for the treatment is Apolitical Driver (Story 1). Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	2.26	2.41	0.17	0.24	0.90	0.92
	(0.09)	(0.09)	(0.02)	(0.03)	(0.02)	(0.02)
Out-Party Driver	0.05		−0.00		0.01	
	(0.13)		(0.03)		(0.03)	
In-Party Driver		0.11		0.02		−0.06
		(0.12)		(0.04)		(0.03)
Num. obs.	509	493	509	493	509	493

Table S7: Main outcome measures vs. whether R knew the attack was told the attack was apolitical or had political motives. Baseline category is apolitical driver (collapsing across stories 1 and 2). Coefficients are from an ordinary least squares regression with HC1 standard errors.

S3.7 Robustness

	Use Violence
(Intercept)	1.58
	(0.06)
Medium SD	0.16
	(0.08)
High SD	0.62
	(0.12)
Num. obs.	1000

Table S8: "How much do you feel it is justified for [R's In-Party] to use violence in advancing their political goals these days?" vs. social desirability (SD) scale. Baseline category is low social desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.17	0.15	0.92
	(0.10)	(0.03)	(0.02)
In-Party Driver	0.29	0.06	−0.08
	(0.17)	(0.05)	(0.04)
Out-Party Driver	0.22	−0.02	−0.06
	(0.17)	(0.04)	(0.04)
Medium SD	0.14	0.03	−0.00
	(0.14)	(0.04)	(0.03)
High SD	0.47	0.20	−0.06
	(0.17)	(0.05)	(0.04)
In-Party Driver * Medium SD	−0.21	0.01	0.01
	(0.24)	(0.07)	(0.06)
Out-Party Driver * Medium SD	−0.18	0.04	0.08
	(0.24)	(0.06)	(0.05)
In-Party Driver * High SD	−0.07	−0.04	0.12
	(0.30)	(0.09)	(0.07)
Out-Party Driver * High SD	−0.86	−0.12	0.17
	(0.31)	(0.09)	(0.06)
Num. obs.	1002	1002	1002

Table S9: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Baseline categories are Apolitical Driver (Story 1) for the treatment condition and low social-desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.02	0.10	0.94
	(0.10)	(0.02)	(0.02)
In-Party Driver	0.02	0.02	−0.04
	(0.16)	(0.04)	(0.04)
Out-Party Driver	0.13	−0.01	−0.02
	(0.18)	(0.04)	(0.03)
Medium Aggression	0.19	0.01	−0.01
	(0.14)	(0.03)	(0.03)
High Aggresion	0.83	0.30	−0.10
	(0.15)	(0.04)	(0.03)
In-Party Driver * Medium Aggression	0.11	0.03	−0.06
	(0.24)	(0.06)	(0.06)
Out-Party Driver * Medium Aggression	−0.18	−0.00	0.05
	(0.26)	(0.06)	(0.05)
In-Party Driver * High Aggresion	0.36	0.06	0.05
	(0.25)	(0.08)	(0.06)
Out-Party Driver * High Aggresion	−0.33	−0.08	0.03
	(0.26)	(0.08)	(0.06)
Num. obs.	1002	1002	1002

Table S10: Main outcome measures vs. the treatment condition interacted with the aggression scale. Baseline categories are Apolitical Driver (Story 1) for the treatment condition and low aggression. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.99	0.06	0.94
	(0.12)	(0.03)	(0.03)
In-Party Driver	−0.28	−0.14	−0.05
	(0.21)	(0.06)	(0.05)
Out-Party Driver	−0.13	−0.04	−0.08
	(0.22)	(0.06)	(0.05)
Pol. Interest	0.40	0.21	−0.04
	(0.28)	(0.08)	(0.06)
In-Party Driver * Pol. Interest	1.05	0.47	0.03
	(0.47)	(0.14)	(0.11)
Out-Party Driver * Pol. Interest	0.28	0.10	0.20
	(0.50)	(0.15)	(0.09)
Num. obs.	769	769	769

Table S11: Main outcome measures vs. the treatment condition interacted with the political interest scale. The baseline category is Apolitical Driver (Story 1) for the treatment condition. The political interest scale is a continuous variable. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.68	−0.04	0.90
	(0.20)	(0.06)	(0.04)
In-Party Driver	−0.07	0.01	−0.03
	(0.37)	(0.12)	(0.08)
Out-Party Driver	0.31	−0.02	0.12
	(0.38)	(0.11)	(0.06)
Moral Threat	0.20	0.07	0.00
	(0.06)	(0.02)	(0.01)
In-Party Driver * Moral Threat	0.07	0.01	−0.01
	(0.11)	(0.03)	(0.02)
Out-Party Driver * Moral Threat	−0.10	−0.01	−0.04
	(0.11)	(0.03)	(0.02)
Num. obs.	1002	1002	1002

Table S12: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are a moral threat to the nation and its people" (Moral Threat). The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.77	−0.04	0.93
	(0.13)	(0.03)	(0.03)
In-Party Driver	0.03	0.05	0.01
	(0.23)	(0.07)	(0.05)
Out-Party Driver	−0.12	0.02	0.05
	(0.22)	(0.05)	(0.04)
Human	0.22	0.09	−0.01
	(0.05)	(0.01)	(0.01)
In-Party Driver * Human	0.04	−0.00	−0.02
	(0.08)	(0.02)	(0.02)
Out-Party Driver * Human	0.04	−0.02	−0.02
	(0.08)	(0.02)	(0.02)
Num. obs.	1002	1002	1002

Table S13: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are less than human" (Human). The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.60	−0.07	0.91
	(0.19)	(0.06)	(0.04)
In-Party Driver	−0.08	0.13	−0.00
	(0.34)	(0.11)	(0.08)
Out-Party Driver	0.13	−0.02	0.04
	(0.34)	(0.10)	(0.07)
Evil	0.25	0.09	−0.00
	(0.06)	(0.02)	(0.01)
In-Party Driver * Evil	0.06	−0.03	−0.02
	(0.10)	(0.04)	(0.03)
Out-Party Driver * Evil	−0.05	−0.00	−0.01
	(0.11)	(0.03)	(0.02)
Num. obs.	993	993	993

Table S14: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are evil" (Evil). The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.20	0.14	0.91
	(0.06)	(0.02)	(0.01)
In-Party Driver	0.20	0.06	−0.06
	(0.11)	(0.03)	(0.03)
Out-Party Driver	0.01	−0.00	−0.01
	(0.11)	(0.03)	(0.03)
Injure Democrats	0.74	0.32	−0.02
	(0.18)	(0.05)	(0.04)
In-Party Driver * Injure Democrats	−0.08	−0.04	0.03
	(0.31)	(0.10)	(0.07)
Out-Party Driver * Injure Democrats	−0.06	−0.17	0.06
	(0.32)	(0.10)	(0.06)
Num. obs.	1002	1002	1002

Table S15: Main outcome measures vs. the treatment condition interacted with a 1 if the respondent responds "Yes" to "Have you ever wished that someone would physically injure one or more Democratic politicians?" (Injure Democrats). The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.20	0.14	0.91
	(0.06)	(0.02)	(0.01)
In-Party Driver	0.20	0.06	−0.06
	(0.11)	(0.03)	(0.03)
Out-Party Driver	0.01	−0.00	−0.01
	(0.11)	(0.03)	(0.03)
Injure Republicans	0.74	0.32	−0.02
	(0.18)	(0.05)	(0.04)
In-Party Driver * Injure Republicans	−0.08	−0.04	0.03
	(0.31)	(0.10)	(0.07)
Out-Party Driver * Injure Republicans	−0.06	−0.17	0.06
	(0.32)	(0.10)	(0.06)
Num. obs.	1002	1002	1002

Table S16: Main outcome measures vs. the treatment condition interacted with a 1 if the respondent responds “Yes” to “Have you ever wished that someone would physically injure one or more Republican politicians?” (Injure Republicans). The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.71	−0.03	0.95
	(0.10)	(0.03)	(0.02)
In-Party Driver	−0.03	−0.02	−0.04
	(0.17)	(0.05)	(0.04)
Out-Party Driver	−0.03	−0.05	−0.01
	(0.18)	(0.04)	(0.04)
Use Violence	0.36	0.13	−0.03
	(0.05)	(0.02)	(0.01)
In-Party Driver * Use Violence	0.10	0.04	−0.01
	(0.08)	(0.03)	(0.02)
Out-Party Driver * Use Violence	−0.01	0.00	0.01
	(0.08)	(0.03)	(0.02)
Num. obs.	1000	1000	1000

Table S17: Main outcome measures vs. the treatment condition interacted with “How much do you feel it is justified for [R’s In-Party] to use violence in advancing their political goals these days?”. The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.79	0.35	0.90
	(0.11)	(0.04)	(0.02)
In-Party Driver	0.30	0.10	−0.06
	(0.20)	(0.07)	(0.05)
Out-Party Driver	0.02	−0.06	−0.06
	(0.19)	(0.06)	(0.05)
Medium AP	−0.68	−0.19	0.01
	(0.15)	(0.05)	(0.03)
High AP	−0.64	−0.24	0.00
	(0.15)	(0.04)	(0.03)
In-Party Driver * Medium AP	−0.05	−0.15	0.00
	(0.26)	(0.08)	(0.07)
Out-Party Driver * Medium AP	−0.09	−0.03	0.09
	(0.26)	(0.07)	(0.06)
In-Party Driver * High AP	−0.29	−0.03	0.02
	(0.26)	(0.08)	(0.06)
Out-Party Driver * High AP	−0.09	0.09	0.10
	(0.26)	(0.08)	(0.06)
Num. obs.	1002	1002	1002

Table S18: Main outcome measures vs. the treatment condition interacted with the affective polarization scale. Baseline categories are Apolitical Driver (Story 1) for the treatment condition and low affective polarization. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S4 Study 2

S4.1 Sample Demographics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
age	1023	47.42	16.79	18	34	61	88
gender	1023						
... Female	523	51%					
... Male	500	49%					
race	1023						
... African American	139	14%					
... Asian	60	6%					
... Native American	25	2%					
... Other (please specify)	58	6%					
... Pacific Islander	2	0%					
... White/Caucasian	739	72%					
pid	1023						
... Democrat	489	48%					
... Republican	534	52%					

Table S19: Summary Statistics for Study 2

S4.2 Treatment Text

Iowa Man Arrested After Shooting A Woman at a [Democratic/Republican/Local Meeting

Steven Wright, 65, was arrested for attempted murder this afternoon in Des Moines. The Iowa local allegedly pulled a gun on a group of [Democrats/Republicans/locals] who were meeting in a neighboring house. Following a confrontation, Wright reportedly shot one of the attendees in the chest.

Two witnesses reported that Wright was upset that [Democrats/Republicans/people] were gathering in what Wright called a [Republican/Democratic/quiet] part of town. After aggressively arguing for several minutes, Wright reportedly aimed his gun at the woman and fired while calling her "a [Democratic/Republican/] maniac bent on ruining Iowa."

The victim later told reporters that she is sure she was shot "because she was trying to help organize [Democrats/Republicans/community events] in her neighborhood."

When deputies arrived, Wright was sitting on a couch next to a shotgun and stated that he was not coming out, the report states. Deputies were able to take him into custody without further incident. They located a pistol on his person with a magazine and six rounds of ammunition, the report continues.

S4.3 Engagement Question

In what state did the event covered by the article you just read occur?

- Iowa
- South Carolina
- Tennessee
- Michigan
- Texas
- Maine
- Oregon

S4.4 Outcome Questions

Do you support or oppose the actions of Steven Wright?

- Strongly Support
- Support
- Neither support nor oppose
- Oppose
- Strongly Oppose

Was the shooter justified or unjustified?

- Justified
- Unjustified

Should the shooter face criminal charges?

- Yes
- No

S4.5 Additional Results

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.53	2.35	0.07	0.26	0.98	0.91
	(0.05)	(0.17)	(0.01)	(0.06)	(0.01)	(0.04)
Democrat Shooter	−0.03	0.19	0.01	0.04	−0.00	−0.04
	(0.07)	(0.23)	(0.02)	(0.08)	(0.01)	(0.06)
Republican Shooter	0.02	0.14	0.05	0.11	−0.02	−0.04
	(0.07)	(0.23)	(0.02)	(0.08)	(0.01)	(0.06)
Engaged Respondent		−1.00		−0.23		0.08
		(0.17)		(0.06)		(0.04)
Democrat Shooter * Engaged Respondent		−0.27		−0.03		0.04
		(0.23)		(0.09)		(0.06)
Republican Shooter * Engaged Respondent		−0.21		−0.09		0.04
		(0.24)		(0.08)		(0.06)
Num. obs.	1023	1023	1023	1023	1023	1023

Table S20: Main outcome measures vs. the treatment condition and Engaged Respondent. The baseline category for the treatment is Apolitical Shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.53	1.54	0.07	0.06	0.98	0.99
	(0.05)	(0.07)	(0.01)	(0.02)	(0.01)	(0.01)
Democrat Shooter	−0.03	−0.07	0.01	0.03	−0.00	−0.01
	(0.07)	(0.10)	(0.02)	(0.03)	(0.01)	(0.01)
Republican Shooter	0.02	0.12	0.05	0.10	−0.02	−0.01
	(0.07)	(0.11)	(0.02)	(0.03)	(0.01)	(0.02)
Republican		−0.03		0.01		−0.02
		(0.10)		(0.03)		(0.02)
Democrat Shooter * Republican		0.08		−0.03		0.01
		(0.14)		(0.04)		(0.02)
Republican Shooter * Republican		−0.19		−0.08		−0.00
		(0.15)		(0.05)		(0.03)
Num. obs.	1023	1023	1023	1023	1023	1023

Table S21: Main outcome measures vs. the treatment condition and party ID. The baseline category for the treatment is Apolitical Shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.51	0.08	0.98
	(0.09)	(0.03)	(0.01)
Democrat Shooter	−0.10	0.00	0.01
	(0.13)	(0.04)	(0.02)
Republican Shooter	0.27	0.10	−0.01
	(0.15)	(0.05)	(0.02)
Weak Dem.	0.12	−0.06	0.02
	(0.15)	(0.03)	(0.01)
Lean Dem.	−0.11	−0.08	0.02
	(0.37)	(0.03)	(0.01)
Lean Rep.	−0.14	−0.08	0.02
	(0.22)	(0.03)	(0.01)
Weak Rep.	−0.03	−0.03	−0.01
	(0.15)	(0.04)	(0.03)
Strong Rep.	0.05	0.01	−0.01
	(0.13)	(0.04)	(0.02)
Democrat Shooter * Weak Dem.	−0.05	0.06	−0.04
	(0.20)	(0.06)	(0.03)
Republican Shooter * Weak Dem.	−0.49	−0.02	−0.01
	(0.21)	(0.07)	(0.03)
Democrat Shooter * Lean Dem.	0.55	0.14	−0.08
	(0.51)	(0.10)	(0.07)
Republican Shooter * Lean Dem.	0.33	0.15	0.01
	(0.96)	(0.22)	(0.02)
Democrat Shooter * Lean Rep.	0.03	−0.00	−0.11
	(0.31)	(0.04)	(0.10)
Republican Shooter * Lean Rep.	−0.18	−0.10	−0.08
	(0.32)	(0.05)	(0.09)
Democrat Shooter * Weak Rep.	0.12	0.00	0.01
	(0.20)	(0.06)	(0.03)
Republican Shooter * Weak Rep.	−0.29	−0.10	0.02
	(0.22)	(0.06)	(0.04)
Democrat Shooter * Strong Rep.	0.09	−0.01	−0.01
	(0.18)	(0.06)	(0.03)
Republican Shooter * Strong Rep.	−0.38	−0.08	−0.02
	(0.20)	(0.06)	(0.04)
Num. obs.	1023	1023	1023

Table S22: Main outcome measures vs. the treatment condition and 7-point party ID. The baseline categories are Apolitical Shooter and Strong Democrat. Coefficients are from an ordinary least squares regression with HC1 standard errors. We note that this analysis was not pre-registered.

	Support	Justifed	Charged
(Intercept)	1.53	0.07	0.98
	(0.05)	(0.01)	(0.01)
In-Party and Partisan	−0.07	0.02	−0.01
	(0.07)	(0.02)	(0.01)
Out-Party and Partisan	0.06	0.05	−0.00
	(0.07)	(0.02)	(0.01)
Num. obs.	1023	1023	1023

Table S23: Main outcome measures vs. the treatment condition. The baseline category for the treatment is Apolitical Shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S4.6 Robustness

	Use Violence
(Intercept)	1.60
	(0.06)
Medium SD	0.03
	(0.08)
High SD	0.06
	(0.10)
Num. obs.	1023

Table S24: "How much do you feel it is justified for [R's In-Party] to use violence in advancing their political goals these days?" vs. social desirability (SD) scale. Baseline category is low social desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.52	0.05	0.98
	(0.09)	(0.02)	(0.01)
In-Party and Partisan	−0.08	0.04	−0.02
	(0.11)	(0.03)	(0.02)
Out-Party and Partisan	−0.04	0.03	0.01
	(0.12)	(0.03)	(0.02)
Medium SD	0.02	0.01	0.00
	(0.11)	(0.03)	(0.02)
High SD	−0.02	0.06	−0.01
	(0.15)	(0.05)	(0.03)
In-Party and Partisan * Medium SD	−0.05	−0.02	0.01
	(0.15)	(0.04)	(0.03)
Out-Party and Partisan * Medium SD	0.14	0.04	−0.03
	(0.16)	(0.05)	(0.03)
In-Party and Partisan * High SD	0.19	−0.01	0.02
	(0.21)	(0.07)	(0.04)
Out-Party and Partisan * High SD	0.19	−0.01	−0.01
	(0.20)	(0.07)	(0.04)
Num. obs.	1023	1023	1023

Table S25: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Baseline categories are Apolitical Shooter for the treatment condition and low social-desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.34	0.02	0.99
	(0.06)	(0.01)	(0.01)
In-Party and Partisan	−0.13	0.00	−0.01
	(0.08)	(0.02)	(0.01)
Out-Party and Partisan	−0.08	0.04	0.00
	(0.08)	(0.02)	(0.01)
Medium Aggression	0.10	0.03	−0.02
	(0.10)	(0.02)	(0.02)
High Aggresion	0.48	0.13	−0.02
	(0.13)	(0.04)	(0.02)
In-Party and Partisan * Medium Aggression	−0.00	0.04	0.01
	(0.13)	(0.04)	(0.03)
Out-Party and Partisan * Medium Aggression	0.28	0.03	−0.01
	(0.15)	(0.04)	(0.03)
In-Party and Partisan * High Aggresion	0.18	0.03	−0.02
	(0.17)	(0.05)	(0.03)
Out-Party and Partisan * High Aggresion	0.20	0.01	−0.01
	(0.18)	(0.06)	(0.03)
Num. obs.	1023	1023	1023

Table S26: Main outcome measures vs. the treatment condition interacted with the aggression scale. Baseline categories are Apolitical Shooter for the treatment condition and low aggression. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.43	−0.01	0.97
	(0.10)	(0.03)	(0.02)
In-Party and Partisan	−0.07	0.05	−0.02
	(0.14)	(0.04)	(0.03)
Out-Party and Partisan	−0.08	0.05	0.01
	(0.16)	(0.05)	(0.03)
Pol. Interest	0.26	0.20	0.02
	(0.26)	(0.09)	(0.04)
In-Party and Partisan * Pol. Interest	−0.01	−0.07	0.02
	(0.36)	(0.11)	(0.06)
Out-Party and Partisan * Pol. Interest	0.39	0.01	−0.04
	(0.43)	(0.14)	(0.06)
Num. obs.	1023	1023	1023

Table S27: Main outcome measures vs. the treatment condition interacted with the political interest scale. The baseline category is Apolitical Shooter for the treatment condition. The political interest scale is a continuous variable. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.17	−0.03	1.03
	(0.09)	(0.03)	(0.02)
In-Party and Partisan	−0.12	−0.02	−0.05
	(0.13)	(0.04)	(0.02)
Out-Party and Partisan	−0.29	−0.06	−0.04
	(0.13)	(0.04)	(0.02)
Use Violence	0.22	0.06	−0.03
	(0.06)	(0.02)	(0.01)
In-Party and Partisan * Use Violence	0.02	0.02	0.02
	(0.08)	(0.03)	(0.02)
Out-Party and Partisan * Use Violence	0.22	0.07	0.02
	(0.09)	(0.03)	(0.02)
Num. obs.	1023	1023	1023

Table S28: Main outcome measures vs. the treatment condition interacted with "How much do you feel it is justified for [R's In-Party] to use violence in advancing their political goals these days?". The baseline category is Apolitical Shooter for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.70	0.11	0.96
	(0.10)	(0.03)	(0.02)
In-Party and Partisan	0.13	0.05	−0.02
	(0.15)	(0.05)	(0.03)
Out-Party and Partisan	0.14	0.05	0.00
	(0.15)	(0.05)	(0.03)
Medium AP	−0.26	−0.07	0.03
	(0.12)	(0.04)	(0.02)
High AP	−0.24	−0.07	0.02
	(0.13)	(0.04)	(0.02)
In-Party and Partisan * Medium AP	−0.32	−0.05	0.02
	(0.17)	(0.05)	(0.03)
Out-Party and Partisan * Medium AP	−0.09	−0.01	−0.00
	(0.19)	(0.06)	(0.03)
In-Party and Partisan * High AP	−0.26	−0.02	0.01
	(0.18)	(0.06)	(0.04)
Out-Party and Partisan * High AP	−0.16	0.01	−0.02
	(0.19)	(0.06)	(0.03)
Num. obs.	1023	1023	1023

Table S29: Main outcome measures vs. the treatment condition interacted with the affective polarization scale. Baseline categories are Apolitical Shooter for the treatment condition and low affective polarization. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S5 Study 3

S5.1 Sample Demographics

Variable	N	Percent
age4	1863	
... 30-44	463	25%
... 45-64	615	33%
... 65+	506	27%
... Under 30	279	15%
gender4	1863	
... Man	807	43%
... Non-binary	12	1%
... Other	1	0%
... Woman	1043	56%
race4	1863	
... Black	253	14%
... Hispanic	256	14%
... Other	113	6%
... White	1241	67%
pid3	1863	
... Democrat	967	52%
... Republican	896	48%

Table S30: Summary Statistics for Study 3

S5.2 Treatment Text

Iowa Man Arrested After Shooting A Woman at a [Democratic/Republican

Steven Wright, 65, was arrested for attempted murder this afternoon in Des Moines. The Iowa local allegedly pulled a gun on a group of [Democrats/Republicans] who were meeting in a neighboring house. Following a confrontation, Wright reportedly shot one of the attendees in the chest.

Two witnesses reported that Wright was upset that [Democrats/Republicans] were gathering in what Wright called a [Republican/Democratic] part of town. After aggressively arguing for several minutes, Wright reportedly aimed his gun at the woman and fired while calling her "a [Democratic/Republican] maniac bent on ruining Iowa."

The victim later told reporters that she is sure she was shot "because she was trying to help organize [Democrats/Republicans] in her neighborhood."

When deputies arrived, Wright was sitting on a couch next to a shotgun and stated that he was not coming out, the report states. Deputies were able to take him into custody without further incident. They located a pistol on his person with a magazine and six rounds of ammunition, the report continues.

S5.3 Engagement Question

In what state did the event covered by the article you just read occur?

- Iowa
- South Carolina
- Tennessee
- Michigan
- Texas
- Maine
- Oregon

S5.4 Outcome Questions

Do you support or oppose the actions of Steven Wright?

- Strongly Support
- Support
- Neither support nor oppose
- Oppose
- Strongly Oppose

Was the shooter justified or unjustified?

- Justified
- Unjustified

Should the shooter face criminal charges?

- Yes
- No

S5.5 Additional Results

Table S31: Study 3: Passing Engagement Test by Incentive Arm

	Dependent variable:
	Passed
incentivizeIncentivized	0.037**
	(0.001, 0.072)
Constant	0.792****
	(0.767, 0.817)
Observations	1,863
R^2	0.002
Adjusted R^2	0.002
Residual Std. Error	0.392 (df = 1861)
F Statistic	4.042** (df = 1; 1861)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table S32: Study 3: Justification, Support and Charges by Political Alignment by Incentive Arm

	Dependent variable:		
	Support	Justification	Charged
	(1)	(2)	(3)
incentivizeIncentivized	0.005	0.027	−0.003
	(−0.112, 0.123)	(−0.007, 0.060)	(−0.026, 0.020)
alignment Out-Party Shooter	−0.133*	0.023	0.023
	(−0.250, −0.016)	(−0.011, 0.057)	(−0.0003, 0.046)
incentivizeIncentivized:alignment Out-Party Shooter	−0.044	−0.049*	0.004
	(−0.210, 0.122)	(−0.097, −0.001)	(−0.028, 0.037)
Constant	1.493***	0.047***	0.962***
	(1.411, 1.574)	(0.024, 0.071)	(0.946, 0.978)
Observations	1,501	1,501	1,501
R^2	0.009	0.003	0.006
Adjusted R^2	0.007	0.001	0.004
Residual Std. Error (df = 1497)	0.816	0.234	0.161
F Statistic (df = 3; 1497)	4.647**	1.373	2.994*
Note:			*p<0.05; **p<0.01; ***p<0.001

Table S33: Trolling, Justifcation, Support and Charges by Political Alignment

	Dependent variable:		
	Support	Justification	Charged
	(1)	(2)	(3)
OutParty Shooter	−0.176***	0.022	0.020*
	(−0.263, −0.089)	(−0.005, 0.048)	(0.001, 0.040)
Shark Bite	2.105***	0.603***	−0.127***
	(1.780, 2.430)	(0.504, 0.702)	(−0.201, −0.053)
Shark Bite X OutParty	0.176	−0.211**	−0.032
	(−0.313, 0.666)	(−0.360, −0.062)	(−0.143, 0.080)
Intercept	1.635***	0.074***	0.945***
	(1.573, 1.697)	(0.055, 0.093)	(0.931, 0.959)
Observations	1,863	1,863	1,863
R^2	0.150	0.093	0.016
Adjusted R^2	0.149	0.092	0.014
Residual Std. Error (df = 1859)	0.945	0.288	0.215
F Statistic (df = 3; 1859)	109.514***	63.546***	9.780***
Note:			*p<0.05; **p<0.01; ***p<0.001

Table S34: Cheerleading, Justifcation, Support and Charges by Political Alignment

	Dependent variable:		
	Support	Justification	Charged
	(1)	(2)	(3)
OutParty Shooter	−0.203***	0.004	0.028**
	(−0.297, −0.110)	(−0.023, 0.032)	(0.009, 0.048)
Cheerleader	0.731***	0.201***	−0.038
	(0.386, 1.076)	(0.099, 0.303)	(−0.111, 0.036)
Cheerleader X OutParty	0.155	0.088	−0.158**
	(−0.304, 0.614)	(−0.048, 0.223)	(−0.256, −0.060)
Intercept	1.685***	0.088***	0.942***
	(1.619, 1.751)	(0.069, 0.108)	(0.928, 0.956)
Observations	1,863	1,863	1,863
R^2	0.034	0.029	0.021
Adjusted R^2	0.033	0.027	0.020
Residual Std. Error (df = 1859)	1.007	0.297	0.215
F Statistic (df = 3; 1859)	22.115***	18.507***	13.589***
Note:			*p<0.05; **p<0.01; ***p<0.001

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.57	2.34	0.08	0.23	0.97	0.92
	(0.04)	(0.14)	(0.01)	(0.04)	(0.01)	(0.02)
Republican Shooter	0.10	0.21	0.03	0.09	−0.03	−0.11
	(0.06)	(0.19)	(0.02)	(0.06)	(0.01)	(0.04)
Engaged Respondent		−0.94		−0.18		0.06
		(0.14)		(0.04)		(0.02)
Republican Shooter * Engaged Respondent		−0.18		−0.08		0.10
		(0.20)		(0.07)		(0.05)
Num. obs.	1863	1863	1863	1863	1863	1863

Table S35: Main outcome measures vs. the treatment condition and Engaged Respondent. The baseline category for the treatment is Democrat shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.57	1.53	0.08	0.09	0.97	0.98
	(0.04)	(0.06)	(0.01)	(0.02)	(0.01)	(0.01)
Republican Shooter	0.10	0.27	0.03	0.02	−0.03	−0.05
	(0.06)	(0.10)	(0.02)	(0.03)	(0.01)	(0.02)
Republican		0.08		−0.02		−0.02
		(0.08)		(0.03)		(0.01)
Republican Shooter * Republican		−0.36		0.02		0.04
		(0.13)		(0.04)		(0.02)
Num. obs.	1863	1863	1863	1863	1863	1863

Table S36: Main outcome measures vs. the treatment condition and party ID. The baseline category for the treatment is Democrat shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.48	0.07	0.98
	(0.08)	(0.02)	(0.01)
Republican Shooter	0.22	0.02	−0.02
	(0.11)	(0.02)	(0.01)
Weak Dem.	0.15	0.06	−0.00
	(0.13)	(0.05)	(0.01)
Weak Rep.	−0.03	−0.03	−0.03
	(0.12)	(0.02)	(0.02)
Strong Rep.	0.22	0.02	−0.02
	(0.10)	(0.03)	(0.01)
Republican Shooter * Weak Dem.	0.13	0.00	−0.08
	(0.21)	(0.07)	(0.04)
Republican Shooter * Weak Rep.	−0.06	0.07	0.01
	(0.18)	(0.05)	(0.04)
Republican Shooter * Strong Rep.	−0.45	0.00	0.00
	(0.15)	(0.04)	(0.02)
Num. obs.	1863	1863	1863

Table S37: Main outcome measures vs. the treatment condition and 7-point party ID (without independents). The baseline category for the treatment is Democrat shooter, and the baseline category for 7-point party ID is Strong Democrat. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.71	0.10	0.94
	(0.05)	(0.01)	(0.01)
Out-Party Shooter	−0.19	0.01	0.02
	(0.06)	(0.02)	(0.01)
Num. obs.	1863	1863	1863

Table S38: Main outcome measures vs. the treatment condition. The baseline category for the treatment is In-Party shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S6 Study 4

S6.1 Sample Demographics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
age	1009	45.2	17.44	18	30	60	90
gender	1009						
... Female	510	51%					
... Male	499	49%					
race	1009						
... African American	160	16%					
... Asian	30	3%					
... Native American	19	2%					
... Other	43	4%					
... Pacific Islander	2	0%					
... White/Caucasian	755	75%					
pid	1009						
... Democrat	540	54%					
... Republican	469	46%					

Table S39: Summary Statistics for Study 4

S6.2 Engagement Vignette and Question

Bringing back sea otters to the Oregon Coast just got a high-level endorsement. The federal budget for this new year includes a directive to study sea otter reintroduction.

The proviso making sea otter fans happy was tucked away deep in the new federal budget. It directs the U.S. Fish and Wildlife Service to study the feasibility and cost of reestablishing the charismatic marine mammals where they were once hunted to near-extinction along the Pacific Coast.

Bob Bailey leads the Elakha Alliance, a group that wants to bring wild sea otters back. His organization instigated the congressional action.

"I'm very pleased. This is very timely," Bailey said in an interview. "It will definitely help U.S. Fish and Wildlife Service develop a strategic approach for how best to conserve and protect sea otters."

What state is receiving funding to study the reintroduction of sea otters?

- Oregon
- Alaska
- Washington
- California
- Texas
- Florida
- Louisiana

S6.3 Treatment Text

Jon James Fishnick was convicted last week of [crime]. He was arrested by police [description].

Table S40: Crime and Crime Description Text for Study 4

Crime	Description
protesting without a permit	after leading a protest against [outparty] on the grounds of the county courthouse. He made no effort to acquire the necessary permit for the protest and refused to leave when asked by police.
vandalism	after he cut down several large signs expressing support for candidates of the [outparty].
assault	for throwing rocks at peaceful [outparty] protesters. Although no one was seriously injured, paramedics bandaged a man with a head wound.
arson	as he attempted to run from a fire he started at the local [outparty] headquarters. Although he waited for the building to close for the night, several adjacent buildings were still occupied.
assault with a deadly weapon	after driving his car into a crow of [outparty] protesters. Although no one was killed, several individuals were seriously injured and one spent a month in the hospital.",
murder	after surveillance footage was found showing Fisknick stabbing a prominent [outparty] to death. Fisknick targeted the victim because he stopped Fisknick from voting in the last election. Fisknick claims the victim wanted to stop [inparty] voters.

S6.4 Outcome Questions

The judge is expected to sentence Fishnick next week. We are interested in what sentence you think is appropriate:

- Community service
- 1 - 3 days in jail
- 4 - 30 days in jail
- 2 - 3 months in jail
- 4 - 6 months in jail
- 7 months to 1 year in jail
- 2 - 5 years in prison
- 6 - 10 years in prison
- 11 - 15 years in prison
- 16 - 20 years in prison
- More than 20 years in prison

Would you support or oppose a pardon for Jon James Fishnick?

- Strongly Support
- Support
- Neither support nor oppose
- Oppose
- Strongly Oppose

S6.5 Additional Results

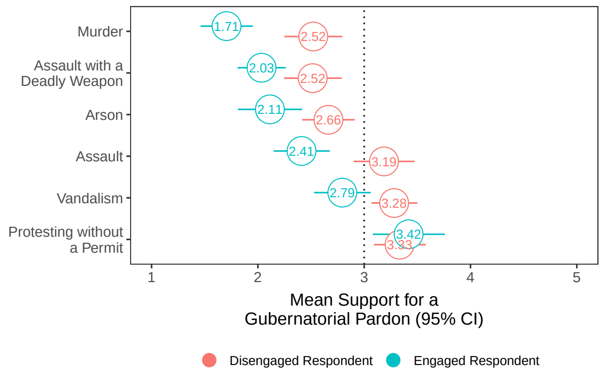

Figure S2: Support for a Mean Support for a Gubernatorial Pardon by Attention

	Pardon	Pardon	Nullify	Nullify
(Intercept)	2.48	2.66	0.04	0.04
	(0.10)	(0.13)	(0.02)	(0.02)
Assault	0.40	0.52	0.27	0.32
	(0.15)	(0.19)	(0.04)	(0.06)
Assault w/Deadly Weapon	−0.20	−0.15	0.04	0.08
	(0.14)	(0.19)	(0.03)	(0.04)
Murder	−0.33	−0.14	0.02	0.04
	(0.14)	(0.19)	(0.02)	(0.03)
Protest w/out Permit	0.88	0.67	0.52	0.47
	(0.14)	(0.18)	(0.04)	(0.05)
Vandalism	0.60	0.62	0.46	0.39
	(0.13)	(0.17)	(0.04)	(0.05)
Engaged Respondent		−0.55		−0.01
		(0.20)		(0.03)
Assault * Engaged Respondent		−0.22		−0.13
		(0.28)		(0.08)
Assault w/Deadly Weapon * Engaged Respondent		0.07		−0.07
		(0.26)		(0.05)
Murder * Engaged Respondent		−0.27		−0.05
		(0.27)		(0.05)
Protest w/out Permit * Engaged Respondent		0.64		0.13
		(0.28)		(0.09)
Vandalism * Engaged Respondent		0.06		0.20
		(0.26)		(0.08)
Num. obs.	991	991	1009	1009

Table S41: Main outcome measures vs. treatment condition and the engagement test. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and failure for the engagement test. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Pardon	Nullify	Nullify
(Intercept)	2.48	2.76	0.04	0.05
	(0.10)	(0.15)	(0.02)	(0.02)
Assault	0.40	0.25	0.27	0.25
	(0.15)	(0.21)	(0.04)	(0.06)
Assault w/Deadly Weapon	−0.20	−0.50	0.04	0.02
	(0.14)	(0.20)	(0.03)	(0.03)
Murder	−0.33	−0.51	0.02	−0.00
	(0.14)	(0.20)	(0.02)	(0.03)
Protest w/out Permit	0.88	0.56	0.52	0.49
	(0.14)	(0.20)	(0.04)	(0.06)
Vandalism	0.60	0.53	0.46	0.42
	(0.13)	(0.19)	(0.04)	(0.06)
Republican		−0.57		−0.01
		(0.19)		(0.03)
Assault * Republican		0.28		0.04
		(0.29)		(0.08)
Assault w/Deadly Weapon * Republican		0.63		0.05
		(0.27)		(0.05)
Murder * Republican		0.38		0.03
		(0.28)		(0.05)
Protest w/out Permit * Republican		0.67		0.06
		(0.28)		(0.09)
Vandalism * Republican		0.14		0.10
		(0.26)		(0.08)
Num. obs.	991	991	1009	1009

Table S42: Main outcome measures vs. treatment condition and party ID. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and Democrats. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.86	0.03
	(0.18)	(0.02)
Assault	0.27	0.34
	(0.26)	(0.07)
Assault w/Deadly Weapon	−0.42	0.06
	(0.26)	(0.04)
Murder	−0.56	0.03
	(0.24)	(0.04)
Protest w/out Permit	0.54	0.45
	(0.24)	(0.07)
Vandalism	0.57	0.42
	(0.22)	(0.06)
Weak Dem.	−0.36	0.07
	(0.35)	(0.07)
Lean Dem.	−0.86	−0.03
	(0.18)	(0.02)
Lean Rep.	−0.46	−0.03
	(0.41)	(0.02)
Weak Rep.	−0.96	−0.03
	(0.29)	(0.02)
Strong Rep.	−0.58	0.02
	(0.24)	(0.04)
Assault * Weak Dem.	0.02	−0.34
	(0.45)	(0.12)
Assault w/Deadly Weapon * Weak Dem.	−0.14	−0.16
	(0.42)	(0.08)
Murder * Weak Dem.	0.29	−0.13
	(0.48)	(0.08)
Protest w/out Permit * Weak Dem.	0.19	0.06
	(0.50)	(0.15)
Vandalism * Weak Dem.	−0.40	−0.06
	(0.45)	(0.17)
Assault * Lean Dem.	−0.02	−0.09
	(0.34)	(0.23)
Assault w/Deadly Weapon * Lean Dem.	0.59	0.10
	(0.57)	(0.16)
Murder * Lean Dem.	−0.10	−0.03
	(0.37)	(0.04)
Protest w/out Permit * Lean Dem.	0.30	0.38
	(0.56)	(0.17)
Vandalism * Lean Dem.	0.10	0.33
	(0.35)	(0.23)
Assault * Lean Rep.	0.33	−0.01
	(0.94)	(0.29)
Assault w/Deadly Weapon * Lean Rep.	−0.38	−0.06
	(0.50)	(0.04)
Murder * Lean Rep.	−0.84	−0.03
	(0.44)	(0.04)
Protest w/out Permit * Lean Rep.	1.56	0.30
	(0.50)	(0.23)
Vandalism * Lean Rep.	−0.37	0.38
	(0.69)	(0.19)
Assault * Weak Rep.	0.26	−0.20
	(0.41)	(0.12)
Assault w/Deadly Weapon * Weak Rep.	0.68	0.00
	(0.39)	(0.06)
Murder * Weak Rep.	0.52	0.04
	(0.41)	(0.06)
Protest w/out Permit * Weak Rep.	0.70	0.20
	(0.39)	(0.12)
Vandalism * Weak Rep.	0.09	0.10
	(0.37)	(0.12)
Assault * Strong Rep.	0.24	−0.01
	(0.36)	(0.10)
Assault w/Deadly Weapon * Strong Rep.	0.64	0.02
	(0.36)	(0.07)
Murder * Strong Rep.	0.49	−0.01
	(0.34)	(0.06)
Protest w/out Permit * Strong Rep.	0.65	0.03
	(0.35)	(0.11)
Vandalism * Strong Rep.	0.21	0.08
	(0.32)	(0.10)
Num. obs.	990	1008

Table S43: Main outcome measures vs. treatment condition and 7-point party ID. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and Strong Democrats. Coefficients are from an ordinary least squares regression with HC1 standard errors. We note that this analysis was not pre-registered.

S6.6 Robustness

	Pardon	Nullify
(Intercept)	2.48	0.04
	(0.17)	(0.02)
Assault	0.28	0.32
	(0.24)	(0.07)
Assault w/Deadly Weapon	−0.58	0.05
	(0.21)	(0.04)
Murder	−0.36	0.04
	(0.23)	(0.04)
Protest w/out Permit	0.71	0.53
	(0.22)	(0.07)
Vandalism	0.39	0.51
	(0.21)	(0.07)
Medium SD	−0.25	−0.01
	(0.22)	(0.03)
High SD	0.44	0.04
	(0.29)	(0.05)
Assault * Medium SD	0.18	−0.04
	(0.32)	(0.10)
Assault w/Deadly Weapon * Medium SD	0.62	−0.02
	(0.29)	(0.05)
Murder * Medium SD	0.02	−0.04
	(0.31)	(0.05)
Protest w/out Permit * Medium SD	0.47	0.02
	(0.30)	(0.09)
Vandalism * Medium SD	0.46	−0.03
	(0.28)	(0.09)
Assault * High SD	0.14	−0.13
	(0.41)	(0.11)
Assault w/Deadly Weapon * High SD	0.41	0.01
	(0.37)	(0.08)
Murder * High SD	0.10	−0.04
	(0.39)	(0.07)
Protest w/out Permit * High SD	−0.02	−0.08
	(0.40)	(0.12)
Vandalism * High SD	0.15	−0.16
	(0.38)	(0.11)
Num. obs.	991	1009

Table S44: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and low social-desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.04	0.06
	(0.14)	(0.03)
Assault	0.60	0.36
	(0.23)	(0.08)
Assault w/Deadly Weapon	−0.27	−0.01
	(0.18)	(0.04)
Murder	−0.33	−0.02
	(0.20)	(0.04)
Protest w/out Permit	1.30	0.59
	(0.21)	(0.07)
Vandalism	0.90	0.56
	(0.19)	(0.07)
Medium Aggression	0.32	−0.02
	(0.21)	(0.04)
High Aggresion	1.00	−0.02
	(0.24)	(0.04)
Assault * Medium Aggression	−0.28	−0.08
	(0.32)	(0.11)
Assault w/Deadly Weapon * Medium Aggression	−0.04	0.04
	(0.27)	(0.06)
Murder * Medium Aggression	−0.28	0.03
	(0.27)	(0.06)
Protest w/out Permit * Medium Aggression	−0.28	−0.04
	(0.32)	(0.11)
Vandalism * Medium Aggression	−0.55	0.02
	(0.28)	(0.10)
Assault * High Aggresion	−0.40	−0.18
	(0.35)	(0.10)
Assault w/Deadly Weapon * High Aggresion	0.42	0.14
	(0.32)	(0.07)
Murder * High Aggresion	0.30	0.06
	(0.33)	(0.06)
Protest w/out Permit * High Aggresion	−0.96	−0.19
	(0.34)	(0.10)
Vandalism * High Aggresion	−0.26	−0.33
	(0.32)	(0.09)
Num. obs.	991	1009

Table S45: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and low aggression. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	1.76	0.05
	(0.19)	(0.03)
Assault	0.54	0.14
	(0.28)	(0.08)
Assault w/Deadly Weapon	0.31	0.04
	(0.26)	(0.05)
Murder	−0.23	−0.03
	(0.27)	(0.04)
Protest w/out Permit	1.68	0.74
	(0.29)	(0.08)
Vandalism	1.17	0.64
	(0.26)	(0.08)
Pol. Interest	1.28	−0.05
	(0.43)	(0.04)
Assault * Pol. Interest	−0.35	0.28
	(0.60)	(0.15)
Assault w/Deadly Weapon * Pol. Interest	−1.16	0.04
	(0.61)	(0.11)
Murder * Pol. Interest	−0.25	0.06
	(0.63)	(0.08)
Protest w/out Permit * Pol. Interest	−1.36	−0.40
	(0.62)	(0.15)
Vandalism * Pol. Interest	−1.31	−0.21
	(0.60)	(0.17)
Num. obs.	750	759

Table S46: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. The political interest scale is a continuous variable. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	1.60	0.06
	(0.37)	(0.05)
Assault	0.60	0.38
	(0.51)	(0.13)
Assault w/Deadly Weapon	−0.66	−0.10
	(0.49)	(0.10)
Murder	−0.69	−0.12
	(0.46)	(0.06)
Protest w/out Permit	1.48	0.73
	(0.49)	(0.13)
Vandalism	1.00	0.78
	(0.46)	(0.12)
Moral Threat	0.25	−0.00
	(0.11)	(0.01)
Assault * Moral Threat	−0.05	−0.03
	(0.15)	(0.04)
Assault w/Deadly Weapon * Moral Threat	0.13	0.04
	(0.14)	(0.03)
Murder * Moral Threat	0.11	0.04
	(0.14)	(0.02)
Protest w/out Permit * Moral Threat	−0.16	−0.07
	(0.14)	(0.04)
Vandalism * Moral Threat	−0.10	−0.10
	(0.13)	(0.03)
Num. obs.	991	1009

Table S47: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are a moral threat to the nation and its people" (Moral Threat). Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	1.85	0.05
	(0.20)	(0.04)
Assault	0.55	0.26
	(0.31)	(0.09)
Assault w/Deadly Weapon	−0.42	−0.03
	(0.27)	(0.06)
Murder	−0.44	−0.08
	(0.27)	(0.04)
Protest w/out Permit	1.50	0.72
	(0.29)	(0.09)
Vandalism	0.52	0.80
	(0.26)	(0.08)
Human	0.24	−0.00
	(0.07)	(0.01)
Assault * Human	−0.06	0.00
	(0.11)	(0.03)
Assault w/Deadly Weapon * Human	0.08	0.03
	(0.10)	(0.02)
Murder * Human	0.04	0.04
	(0.10)	(0.02)
Protest w/out Permit * Human	−0.23	−0.08
	(0.10)	(0.03)
Vandalism * Human	0.02	−0.12
	(0.09)	(0.03)
Num. obs.	991	1009

Table S48: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are less than human" (Human). Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.18	0.08
	(0.34)	(0.05)
Assault	0.15	0.36
	(0.50)	(0.13)
Assault w/Deadly Weapon	−0.83	−0.04
	(0.45)	(0.09)
Murder	−0.76	−0.04
	(0.44)	(0.08)
Protest w/out Permit	1.48	0.72
	(0.47)	(0.13)
Vandalism	0.08	0.78
	(0.42)	(0.11)
Evil	0.10	−0.01
	(0.11)	(0.02)
Assault * Evil	0.07	−0.03
	(0.16)	(0.04)
Assault w/Deadly Weapon * Evil	0.21	0.03
	(0.15)	(0.03)
Murder * Evil	0.13	0.02
	(0.14)	(0.02)
Protest w/out Permit * Evil	−0.21	−0.07
	(0.16)	(0.04)
Vandalism * Evil	0.18	−0.11
	(0.14)	(0.04)
Num. obs.	989	1007

Table S49: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are evil" (Evil). Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.28	0.05
	(0.10)	(0.02)
Assault	0.39	0.32
	(0.16)	(0.05)
Assault w/Deadly Weapon	−0.17	0.04
	(0.14)	(0.03)
Murder	−0.35	0.01
	(0.14)	(0.03)
Protest w/out Permit	1.02	0.54
	(0.15)	(0.05)
Vandalism	0.65	0.53
	(0.14)	(0.05)
Injure Democrats	0.99	−0.02
	(0.27)	(0.03)
Assault * Injure Democrats	−0.20	−0.21
	(0.36)	(0.08)
Assault w/Deadly Weapon * Injure Democrats	−0.04	0.02
	(0.38)	(0.06)
Murder * Injure Democrats	0.13	0.02
	(0.38)	(0.06)
Protest w/out Permit * Injure Democrats	−0.67	−0.12
	(0.37)	(0.11)
Vandalism * Injure Democrats	−0.03	−0.36
	(0.36)	(0.09)
Num. obs.	991	1009

Table S50: Main outcome measures vs. the treatment condition interacted with a 1 if the respondent responds “Yes” to “Have you ever wished that someone would physically injure one or more Democratic politicians?” (Injure Democrats). Pardon is a Likert scale “Would you support or oppose a pardon for Jon James Fishnick?” Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.28	0.05
	(0.10)	(0.02)
Assault	0.39	0.32
	(0.16)	(0.05)
Assault w/Deadly Weapon	−0.17	0.04
	(0.14)	(0.03)
Murder	−0.35	0.01
	(0.14)	(0.03)
Protest w/out Permit	1.02	0.54
	(0.15)	(0.05)
Vandalism	0.65	0.53
	(0.14)	(0.05)
Injure Republicans	0.99	−0.02
	(0.27)	(0.03)
Assault * Injure Republicans	−0.20	−0.21
	(0.36)	(0.08)
Assault w/Deadly Weapon * Injure Republicans	−0.04	0.02
	(0.38)	(0.06)
Murder * Injure Republicans	0.13	0.02
	(0.38)	(0.06)
Protest w/out Permit * Injure Republicans	−0.67	−0.12
	(0.37)	(0.11)
Vandalism * Injure Republicans	−0.03	−0.36
	(0.36)	(0.09)
Num. obs.	991	1009

Table S51: Main outcome measures vs. the treatment condition interacted with a 1 if the respondent responds “Yes” to “Have you ever wished that someone would physically injure one or more Republican politicians?” (Injure Republicans). Pardon is a Likert scale “Would you support or oppose a pardon for Jon James Fishnick?” Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	1.63	0.00
	(0.15)	(0.02)
Assault	0.37	0.29
	(0.22)	(0.07)
Assault w/Deadly Weapon	−0.25	0.03
	(0.20)	(0.04)
Murder	−0.37	0.02
	(0.21)	(0.04)
Protest w/out Permit	1.56	0.71
	(0.23)	(0.07)
Vandalism	0.87	0.78
	(0.21)	(0.07)
Use Violence	0.43	0.02
	(0.07)	(0.01)
Assault * Use Violence	0.02	−0.01
	(0.09)	(0.03)
Assault w/Deadly Weapon * Use Violence	0.07	0.01
	(0.10)	(0.02)
Murder * Use Violence	0.08	0.00
	(0.10)	(0.02)
Protest w/out Permit * Use Violence	−0.33	−0.11
	(0.11)	(0.03)
Vandalism * Use Violence	−0.13	−0.16
	(0.10)	(0.03)
Num. obs.	990	1008

Table S52: Main outcome measures vs. the treatment condition interacted with “How much do you feel it is justified for [R’s In-Party] to use violence in advancing their political goals these days?”. Pardon is a Likert scale “Would you support or oppose a pardon for Jon James Fishnick?” Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.94	0.05
	(0.18)	(0.03)
Assault	0.51	0.27
	(0.26)	(0.07)
Assault w/Deadly Weapon	−0.28	0.07
	(0.26)	(0.05)
Murder	−0.27	0.07
	(0.26)	(0.05)
Protest w/out Permit	0.44	0.44
	(0.23)	(0.07)
Vandalism	0.51	0.27
	(0.24)	(0.07)
Medium AP	−0.52	−0.00
	(0.25)	(0.04)
High AP	−0.92	−0.01
	(0.22)	(0.04)
Assault * Medium AP	−0.30	−0.10
	(0.34)	(0.10)
Assault w/Deadly Weapon * Medium AP	0.06	−0.03
	(0.34)	(0.07)
Murder * Medium AP	−0.25	−0.10
	(0.35)	(0.06)
Protest w/out Permit * Medium AP	0.58	0.10
	(0.34)	(0.11)
Vandalism * Medium AP	−0.03	0.25
	(0.33)	(0.10)
Assault * High AP	0.01	0.09
	(0.35)	(0.10)
Assault w/Deadly Weapon * High AP	0.24	−0.04
	(0.33)	(0.06)
Murder * High AP	0.17	−0.08
	(0.32)	(0.06)
Protest w/out Permit * High AP	0.81	0.15
	(0.33)	(0.10)
Vandalism * High AP	0.43	0.32
	(0.31)	(0.10)
Num. obs.	991	1009

Table S53: Main outcome measures vs. the treatment condition interacted with the affective polarization scale. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and low affective polarization. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S7 Study 5

Our second PAP includes a study 5. We completed this study, but trimmed it from the main manuscript for space and for clarity. Our plan is to consider this for a future publication, but we present the major result below and report all preregistered analysis to comply with our PAP.

In this study we asked individuals to estimate how many Democrats and Republicans support political violence. One half of the sample just answered these questions. The other half was offered a cash incentive for being within 3 percentage points of the correct answer (the group mean from the study). We presented the same engagement vignette from study 3 (see page S6.2).

The major result is that individuals dramatically overestimate group support for political violence among their own party (see Figure S3) and among the out-party. This is consistent for both those offered an incentive and those not offered the incentive.

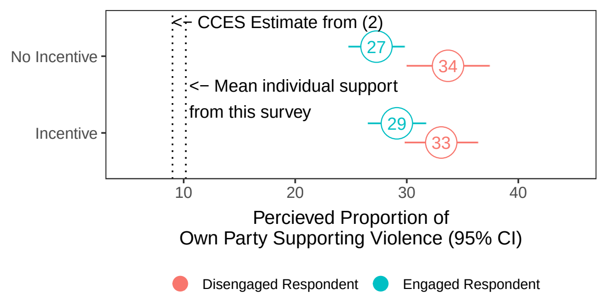

Figure S3: Respondents Dramatically Overestimate Group Support for Violence.

S7.1 Sample Demographics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
age	1030	46.67	16.97	18	32	61	92
gender	1030						
... Female	524	51%					
... Male	506	49%					
race	1030						
... African American	155	15%					
... Asian	72	7%					
... Native American	27	3%					
... Other (please specify)	57	6%					
... Pacific Islander	2	0%					
... White/Caucasian	717	70%					
pid	1030						
... Democrat	518	50%					
... Republican	512	50%					

Table S54: Summary Statistics for Study 5

S7.2 Engagement Vignette and Question

Bringing back sea otters to the Oregon Coast just got a high-level endorsement. The federal budget for this new year includes a directive to study sea otter reintroduction.

The proviso making sea otter fans happy was tucked away deep in the new federal budget. It directs the U.S. Fish and Wildlife Service to study the feasibility and cost of reestablishing the charismatic marine mammals where they were once hunted to near-extinction along the Pacific Coast.

Bob Bailey leads the Elakha Alliance, a group that wants to bring wild sea otters back. His organization instigated the congressional action.

"I'm very pleased. This is very timely," Bailey said in an interview. "It will definitely help U.S. Fish and Wildlife Service develop a strategic approach for how best to conserve and protect sea otters."

What state is receiving funding to study the reintroduction of sea otters?

- Oregon
- Alaska
- Washington
- California
- Texas
- Florida
- Louisiana

S7.3 Treatment Text

S7.3.1 No Incentive Prompt

We are interested in how Americans perceive supporters of the two main political parties.

Just give us your best guesses to the questions below.

(Please do not look answer up though; we are interested in your perceptions! Each page has a time limit before it auto-advances.)

S7.3.2 Incentive Prompt

We are interested in how Americans perceive supporters of the two main political parties.

Just give us your best guesses to the questions below.

We will give you $.50 for each response that comes within 3 percentage points of the correct answer.

(Please do not look answer up though; we are interested in your perceptions! Each page has a time limit before it auto-advances.)

S7.4 Outcome Questions

What percentage of Republicans do you think...? (forced sum to 100%)

- Support using violence in advancing their political goals
- Oppose using violence in advancing their political goals

What percentage of Democrats do you think...? (forced sum to 100%)

- Support using violence in advancing their political goals
- Oppose using violence in advancing their political goals

S7.5 Additional Results

Note these shorthand labels for the main outcome measures:

- "Rep. Dist." = the distance between the respondent's perception for Republicans and the true percentage of Republicans who support using violence.
- "Dem. Dist." = the distance between the respondent's perception for Democrats and the true percentage of Democrats who support using violence.
- "Rep. Sup." = respondent's perception of the percentage of Republicans who support using violence.
- "Dem. Sup." = respondent's perception of the percentage of Democrats who support using violence.
- "In-Party Sup." = respondent's perception of the percentage of members of their in-party who support using violence.
- "Out-Party. Sup." = respondent's perception of the percentage of members of their out-party who support using violence.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	30.38	29.06	36.22	35.01	29.71	41.52
	(1.21)	(0.93)	(1.35)	(1.10)	(1.07)	(1.32)
Incentivized	−2.01	2.06	−1.19	3.15	0.90	1.06
	(1.64)	(1.30)	(1.82)	(1.50)	(1.49)	(1.75)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S55: Main outcome measures vs. treatment condition. Baseline category for treatment condition is No Incentive. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	34.42	29.51	40.30	35.03	33.70	41.64
	(2.02)	(1.63)	(2.27)	(1.91)	(1.88)	(2.28)
Incentivized	−4.60	0.73	−3.31	2.32	−0.61	−0.39
	(2.69)	(2.24)	(2.97)	(2.57)	(2.51)	(2.98)
Engaged Respondent	−6.49	−0.73	−6.57	−0.04	−6.41	−0.19
	(2.51)	(1.98)	(2.81)	(2.33)	(2.27)	(2.79)
Incentivized * Engaged Respondent	4.16	2.13	3.41	1.33	2.43	2.31
	(3.39)	(2.75)	(3.75)	(3.16)	(3.11)	(3.68)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S56: Main outcome measures vs. treatment condition and Engaged Respondent. Baseline categories are No Incentive and Disengaged Respondent. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.
(Intercept)	43.90	31.32	51.81	38.43
	(1.80)	(1.28)	(1.90)	(1.45)
Incentivized	−3.48	1.22	−3.19	1.69
	(2.39)	(1.80)	(2.52)	(2.01)
Republican	−26.32	−4.41	−30.35	−6.65
	(2.14)	(1.86)	(2.36)	(2.17)
Incentivized * Republican	1.25	1.45	2.07	2.58
	(2.87)	(2.59)	(3.14)	(2.98)
Num. obs.	1030	1030	1030	1030

Table S57: Main outcome measures vs. treatment condition and party ID. Baseline categories are No Incentive and Democrat. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.
(Intercept)	46.42	31.82	54.28	38.91
	(2.23)	(1.65)	(2.38)	(1.86)
Incentivized	−5.51	1.83	−5.13	2.61
	(2.99)	(2.30)	(3.16)	(2.54)
Weak Dem.	−8.10	−2.02	−8.09	−2.18
	(3.82)	(2.74)	(4.04)	(3.13)
Lean Dem.	1.14	3.62	2.27	5.53
	(10.87)	(5.52)	(10.90)	(5.59)
Lean Rep.	−27.80	−2.36	−29.28	−7.37
	(5.79)	(5.76)	(6.42)	(7.87)
Weak Rep.	−25.47	−6.08	−28.77	−8.09
	(3.04)	(2.58)	(3.40)	(3.04)
Strong Rep.	−31.24	−4.34	−35.92	−6.46
	(2.63)	(2.52)	(2.93)	(2.91)
Incentivized * Weak Dem.	7.93	−1.35	7.97	−1.95
	(5.07)	(3.85)	(5.34)	(4.35)
Incentivized * Lean Dem.	−12.84	−6.98	−15.83	−10.55
	(14.10)	(8.30)	(14.64)	(9.30)
Incentivized * Lean Rep.	−1.46	1.35	−0.37	6.21
	(6.79)	(8.32)	(7.48)	(10.21)
Incentivized * Weak Rep.	4.41	0.07	5.80	−0.31
	(4.23)	(3.71)	(4.66)	(4.35)
Incentivized * Strong Rep.	3.52	1.07	3.92	2.23
	(3.52)	(3.42)	(3.88)	(3.89)
Num. obs.	1030	1030	1030	1030

Table S58: Main outcome measures vs. treatment condition and 7-point party ID. Baseline categories are No Incentive and Strong Democrat Democrat. Coefficients are from an ordinary least squares regression with HC1 standard errors. We note that this analysis was not pre-registered.

S7.6 Robustness

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	30.53	29.94	35.75	35.44	28.36	42.83
	(2.02)	(1.64)	(2.28)	(1.93)	(1.80)	(2.27)
Incentivized	−3.10	2.76	−2.08	3.91	1.49	0.34
	(2.82)	(2.26)	(3.14)	(2.63)	(2.54)	(3.06)
Medium SD	−0.74	−0.86	0.30	0.22	0.46	0.07
	(2.75)	(2.17)	(3.08)	(2.53)	(2.40)	(3.01)
High SD	0.73	−2.55	1.61	−2.49	5.50	−6.37
	(3.24)	(2.45)	(3.64)	(2.94)	(3.00)	(3.53)
Incentivized * Medium SD	0.04	−1.14	−0.74	−1.50	−0.13	−2.12
	(3.74)	(2.97)	(4.15)	(3.42)	(3.36)	(4.00)
Incentivized * High SD	5.95	−0.95	6.55	−0.70	−2.33	8.18
	(4.48)	(3.57)	(4.94)	(4.17)	(4.16)	(4.81)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S59: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Baseline categories are No Incentive for the treatment condition and low social-desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	26.34	30.93	31.28	36.32	27.29	40.31
	(1.96)	(1.70)	(2.23)	(2.02)	(1.88)	(2.26)
Incentivized	−2.36	0.75	−1.33	2.36	0.71	0.32
	(2.66)	(2.32)	(2.99)	(2.70)	(2.56)	(3.01)
Medium Aggression	0.91	−2.89	1.81	−1.68	1.76	−1.63
	(2.94)	(2.32)	(3.29)	(2.73)	(2.69)	(3.21)
High Aggresion	10.59	−2.86	12.35	−2.29	5.32	4.73
	(2.83)	(2.30)	(3.17)	(2.72)	(2.57)	(3.20)
Incentivized * Medium Aggression	1.71	0.75	1.71	−0.74	−1.36	2.33
	(3.92)	(3.19)	(4.35)	(3.69)	(3.64)	(4.24)
Incentivized * High Aggresion	0.72	3.57	0.11	3.47	2.77	0.80
	(3.91)	(3.22)	(4.35)	(3.71)	(3.62)	(4.30)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S60: Main outcome measures vs. the treatment condition interacted with the aggression scale. Baseline categories are No Incentive for the treatment condition and low aggression. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	28.14	26.46	33.26	31.61	27.57	37.29
	(2.07)	(1.56)	(2.32)	(1.84)	(1.88)	(2.25)
Incentivized	−3.55	3.32	−2.96	4.15	0.48	0.72
	(3.02)	(2.39)	(3.35)	(2.75)	(2.81)	(3.21)
Pol. Interest	6.04	6.99	7.99	9.18	5.77	11.40
	(4.65)	(3.44)	(5.09)	(3.91)	(4.18)	(4.80)
Incentivized * Pol. Interest	3.59	−3.60	4.07	−3.06	0.76	0.25
	(6.71)	(5.25)	(7.29)	(5.83)	(6.14)	(6.78)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S61: Main outcome measures vs. the treatment condition interacted with the political interest scale. The baseline category is No Incentive for the treatment condition. The political interest scale is a continuous variable. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	22.93	31.83	27.53	37.83	26.06	39.30
	(2.08)	(1.68)	(2.33)	(1.98)	(1.93)	(2.35)
Incentivized	−1.21	1.26	0.13	2.12	1.38	0.86
	(2.78)	(2.25)	(3.08)	(2.61)	(2.58)	(3.04)
Use Violence	4.49	−1.68	5.24	−1.70	2.20	1.34
	(1.06)	(0.82)	(1.16)	(0.96)	(0.94)	(1.21)
Incentivized * Use Violence	−0.54	0.50	−0.86	0.64	−0.32	0.09
	(1.38)	(1.07)	(1.52)	(1.23)	(1.24)	(1.52)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S62: Main outcome measures vs. the treatment condition interacted with "How much do you feel it is justified for [R's In-Party] to use violence in advancing their political goals these days?". The baseline category is No Incentive for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	31.89	28.94	38.26	35.25	34.32	39.20
	(1.86)	(1.57)	(2.08)	(1.81)	(1.85)	(2.03)
Incentivized	−0.62	0.80	0.08	1.46	−0.47	2.01
	(2.59)	(2.22)	(2.87)	(2.53)	(2.60)	(2.78)
Medium AP	−2.12	2.13	−1.95	2.08	−4.67	4.81
	(2.83)	(2.19)	(3.12)	(2.57)	(2.58)	(3.00)
High AP	−2.63	−1.74	−4.49	−2.84	−9.81	2.49
	(2.97)	(2.35)	(3.34)	(2.74)	(2.61)	(3.31)
Incentivized * Medium AP	−6.23	1.42	−6.63	1.96	0.29	−4.96
	(3.74)	(3.11)	(4.12)	(3.57)	(3.57)	(4.01)
Incentivized * High AP	2.47	2.27	3.29	3.05	4.50	1.84
	(4.12)	(3.24)	(4.59)	(3.73)	(3.69)	(4.41)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S63: Main outcome measures vs. the treatment condition interacted with the affective polarization scale. Baseline categories are No Incentive for the treatment condition and low affective polarization. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S8 Passing Engagement and Demographic Traits

One concern is that our engagement measure is acting as a proxy for demographic differences. To address this concern we predict passing the engagement check with a series of demographic variables: sex (male or female), age, race (white or non-white), partisanship (Democrat or Republican), education (less than high school, high school, college, and advanced degree) and income. We find no systematic effects. Age predicts passing in study 1 and study 2. In study 1 white respondents and more educated respondents are more likely to pass, though this are no similar effects in study 2 and study 3.

Table S64: Predicting Passing the Engagement Check Studies 1-3

	Study 1	Study 2	Study 3
	(1)	(2)	(3)
Age	0.008	0.001	0.007
	(0.001)	(0.001)	(0.001)
Male	0.009	−0.044	−0.003
	(0.029)	(0.026)	(0.032)
White	0.100	0.015	0.067
	(0.037)	(0.032)	(0.039)
Republican	−0.025	0.007	−0.027
	(0.030)	(0.028)	(0.033)
Advanced Degree	0.199	0.048	−0.092
	(0.100)	(0.087)	(0.112)
College	0.290	0.028	−0.102
	(0.095)	(0.082)	(0.109)
High School	0.242	0.025	−0.108
	(0.093)	(0.081)	(0.107)
$100k +	−0.017	0.007	0.067
	(0.046)	(0.040)	(0.050)
$30k-39k	0.018	0.041	0.043
	(0.050)	(0.044)	(0.057)
$40k-49k	0.004	0.083	0.051
	(0.053)	(0.049)	(0.058)
$50k-59k	−0.024	0.029	0.004
	(0.057)	(0.047)	(0.060)
$60k-69k	0.059	−0.026	0.066
	(0.064)	(0.053)	(0.072)
$70k-79k	−0.119	−0.107	−0.033
	(0.061)	(0.054)	(0.060)
$80k-89k	0.066	0.018	0.011
	(0.068)	(0.059)	(0.088)
$90k-99k	0.062	−0.005	0.044
	(0.064)	(0.059)	(0.075)
Intercept	0.020	0.721	0.135
	(0.096)	(0.087)	(0.112)
Observations	1,002	1,023	1,009

S9 Correlates of Violence (Aggression Tables)

Table S65: Support for Violence by Aggression

	Dependent variable:			
	Our Measure (Engaged)	Our Measure (Full Sample)	Kalmoe-Mason (Engaged)	Kalmoe-Ma
	(1)	(2)	(3)	
Buss Perry (0-1)	0.203***	0.426***	0.667***	0
	(0.095, 0.312)	(0.313, 0.539)	(0.517, 0.817)	(0.6
Intercept	0.049**	0.031	0.093***	
	(0.015, 0.083)	(−0.008, 0.070)	(0.045, 0.141)	(0.0
Observations	279	339	833	
R^2	0.047	0.140	0.084	
Adjusted R^2	0.043	0.137	0.083	
Residual Std. Error	0.178 (df = 277)	0.227 (df = 337)	0.422 (df = 831)	0.425
F Statistic	13.527*** (df = 1; 277)	54.723*** (df = 1; 337)	76.096*** (df = 1; 831)	157.070**

Note: *p<0.05; **p

Table S66: Support for Violence by Aggression Binned in Terciles

	Dependent variable:			
	Our Measure (Engaged)	Our Measure (Full Sample)	Kalmoe-Mason (Engaged)	Kalmoe-M
	(1)	(2)	(3)	
Buss Perry - Medium	0.067**	0.095**	0.149***	
	(0.018, 0.117)	(0.035, 0.156)	(0.080, 0.217)	(0
Buss Perry - High	0.085**	0.170***	0.296***	
	(0.034, 0.136)	(0.110, 0.230)	(0.225, 0.368)	(0
Intercept	0.056***	0.066**	0.130***	
	(0.024, 0.089)	(0.026, 0.106)	(0.083, 0.177)	(0
Observations	279	339	833	
R^2	0.044	0.086	0.074	
Adjusted R^2	0.037	0.080	0.072	
Residual Std. Error	0.178 (df = 276)	0.234 (df = 336)	0.425 (df = 830)	0.43
F Statistic	6.321** (df = 2; 276)	15.720*** (df = 2; 336)	33.184*** (df = 2; 830)	62.507

Note: *p<0.05; **

S10 Partial Identification under Nonignorable Engagement

Suppose we observe survey question outcomes Y_i measuring support for political violence for each respondent i. Some respondents are engaged ($E_i = 1$) while other respondents are disengaged ($E_i = 0$); engagement at the time of the survey is thought to be a function of the incentives of the survey, the respondent, the time the respondent takes the survey, and so on. In theory, each respondent has an engaged potential outcome $Y_i(1)$ that they respond with if they are engaged when taking the survey and a disengaged potential outcome $Y_i(0)$ that they respond with if they are disengaged when taking the survey. That is,

$$Y_i = \begin{cases} Y_i(1) & E_i = 1 \\ Y_i(0) & E_i = 0 \end{cases} \tag{1}$$

Note that, by using potential outcomes (POs), we capture the fact that the respondents who are engaged at the time of the survey might by systematically different from respondents who are disengaged at the time of the survey. That is, $\mathbb{E}[Y_i(1) \mid E_i = 1] \neq \mathbb{E}[Y(1) \mid E_i = 0]$. This is analogous to treatment ignorability (where E_i is the "treatment") in causal inference.

The target, or estimand, of our analysis is the population-level support for violence on the engaged PO, $\mathbb{E}[Y(1)]$. The disengaged support for violence $Y_i(0)$ is not necessarily related to $Y_i(1)$ — it might be a random response or based on a fixed-response strategy such as always picking the middle position on a Likert scale — so it is ignored in the following analysis.

In our model, engagement E_i is not direclty observed. We only observe whether the respondent passes an engagement check: $C_i = 1$ if the check is passed and $C_i = 0$ if the check is failed. $P(C_i = 1)$ is the share of respondents who pass the check in the population. We assume that engaged respondents pass the check with probability 1, and disengaged respondents pass the check with probability β:

$$P(C_i = 1 \mid E_i = 1) = 1 \tag{2}$$

$$P(C_i = 1 \mid E_i = 0) = \beta, \tag{3}$$

where β is known, such as $\beta = 1/K$ for an engagement check with K response options. Given this structure, the share of respondents who are engaged, $\pi = P(E_i = 1)$, is point identified:

$$P(C_i = 1) = \pi + (1 - \pi)\beta \implies \pi = \frac{P(C_i = 1) - \beta}{1 - \beta}. \tag{4}$$

Note that $\pi \leq P(C_i = 1)$ with a strict inequality if $\beta > 0$. This captures the fact that some of the respondents who pass the check are disengaged (and passed the check by mere chance). We make one further assumption that the disengaged PO is (mean) independent of passing the check among disengaged respondents:

$$\mathbb{E}[Y_i(0) \mid C_i = 0, E_i = 0] = \mathbb{E}[Y_i(0) \mid C_i = 1, E_i = 0]. \tag{5}$$

That is, disengaged respondents who pass the check shirk on Y_i in the same way as disengaged respondents who fail the check. Thus, the researcher should randomize the check response options to guarantee shirking strategies are independent (over the disengaged population) of passing the check.

To obtain identification results for the target $\mathbb{E}[Y_i(1)]$, we first point identify $\mu = \mathbb{E}[Y_i(1) \mid E_i = 1]$. To see how, note that the population average observed outcome satisfies

$$\begin{aligned}
\mathbb{E}[Y_i] &= \mathbb{E}[Y_i \mid E_i = 1]\pi + \mathbb{E}[Y_i \mid E_i = 0](1 - \pi) \\
&= \mathbb{E}[Y_i(1) \mid E_i = 1]\pi + \mathbb{E}[Y_i(0) \mid E_i = 0](1 - \pi) \\
&= \mu\pi + \mathbb{E}[Y_i(0) \mid E_i = 0, C_i = 0](1 - \pi) \\
&= \mu\pi + \mathbb{E}[Y_i(0) \mid C_i = 0](1 - \pi),
\end{aligned}$$

since $C_i = 0 \implies E_i = 0$. This leads to

$$\mu = \frac{\mathbb{E}[Y_i] - \mathbb{E}[Y_i \mid C_i = 0](1 - \pi)}{\pi} \tag{6}$$

With this result, we can partially identify $\mathbb{E}[Y_i(1)]$ using an analogous tower argument.

$$\begin{aligned}
\theta = \mathbb{E}[Y_i(1)] &= \mathbb{E}[Y_i(1) \mid E_i = 1]\pi + \mathbb{E}[Y_i(1) \mid E_i = 0](1 - \pi) \\
&= \mu\pi + \lambda(1 - \pi)
\end{aligned}$$

where $\lambda = \mathbb{E}[Y_i(1) \mid E_i = 0]$ is the population average engaged PO. Putting this together, we have

$$\begin{aligned}\theta(\lambda) &= \mathbb{E}[Y_i] + (\lambda - \mathbb{E}[Y_i \mid C_i = 0])(1-\pi) \\ &= \mathbb{E}[Y_i] + \frac{\lambda}{1-\beta}\mathbb{E}[(1-C_i)] - \frac{1}{1-\beta}\mathbb{E}[Y_i(1-C_i)]\end{aligned}$$

where the first expression for $\theta(\lambda)$ is more interpretable in terms of the model, but the second expression is written in terms of statistical targets (and suggests the Delta method). Note that one should not analyze this last expression as a function of β all-else-held-fixed, since the distribution of C_i depends on β.

If $\lambda \in \Lambda$, then the partial identification bounds are $[\theta_l, \theta_u] = [\inf_{\lambda\in\Lambda}\theta(\lambda), \sup_{\lambda\in\Lambda}\theta(\lambda)] = [\theta(\inf\Lambda), \theta(\sup\Lambda)]$ by monotonicity. Notably, if the outcomes Y_i are binary, and $\Lambda = [a, b]$ where $a \geq 0, b \leq 1$, then $[\theta_l, \theta_u] = [\theta(a), \theta(b)]$.

To construct confidence intervals, we adapt the results of **(author?)** (3, §4). The sampling distributions of $\hat{\theta}_l, \hat{\theta}_u$ can be obtained from a straightforward application of the Delta method on the vector of sample means $\frac{1}{N}\sum_{i=1}^{N}(Y_i, F_i, Y_iF_i)'$ where $F_i = 1 - C_i$.

Table S67: Crosswalk between PAP study labels and manuscript study labels

PAP	PAP Label	Manuscript Label
PAP 1	Study 1	Study 1
PAP 1	Study 2	Study 4
PAP 2	Study 1 (Replication)	Study 2
PAP 2	Study 3	Study 45 (Appendix only)
PAP 3	Study 1 (Replication)	Study 3

S11 Pre Analysis Plans

Note: the study labels in these PAPs does not match the final document. We provide a crosswalk in Table S67.

S11.1 PAP1 (Study 1 and Study 4

Pre-Analysis Plan: Support for Political Violence

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September 7, 2021

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1 Preliminary Notes

- This is the pre-analysis plan for a survey experiment on support for political violence. There are two experiments in the survey.
- All of the code excerpted below is included in our upload to OSF along with our PAP. We excerpt it into the PAP to facilitate peer review.
- In the code that follows we use raw codings, though we may standardize for interpretability.
- We will conduct a multiple testing correction following Anderson (2008).
- This is an updated PAP based on a pretest of 50 respondents. It corrects several coding issues and specifies that we will also look at results by attentiveness.

2 Data Cleaning

We will clean the data for the survey as follows:

```
library(tidyverse)
library(psy)
library(qualtRics)
library(gtools)
data <- read_csv("data/data.csv")

table(data$gc)
data <- data %>%
filter(gc==1)

#recode leaners
data$Q10[data$Q11 == "Democratic Party"] <- "Democrat"
data$Q10[data$Q11 == "Republican Party"] <- "Republican"
data$pid <- data$Q10
data$pid <- as.factor(data$pid)

# covariates
data$gender <- as.factor(data$Q4)
data$income <- as.factor(data$Q7)
data$education <- as.factor(data$Q8)
data$age <- data$Q14
data$race <- data$Q5

# strong partisans
data$Q12<-recode(data$Q12, "Strong Republican" = 1, "Not a strong Republican" = 0)
data$Q13<-recode(data$Q13, "Strong Democrat" = 1, "Not a strong Democrat" = 0)
```

```
data$strongpartisan <- 0
data$strongpartisan[data$pid=="Republican"] <- data$Q12[data$pid=="Republican"]
data$strongpartisan[data$pid=="Democrat"] <- data$Q13[data$pid=="Democrat"]

#recode experiments and conditions

data$experiment <- recode(data$experiment, "1" = "Vignette", "2" = "Sentencing")

#study 1
data$cell <- NA
data$cell[data$version == 1 & data$partisantreatment == 1] <-
"Republican and Partisan"
data$cell[data$version == 2 & data$partisantreatment == 1] <-
"Republican and Non-Partisan"
data$cell[data$version == 1 & data$partisantreatment == 2] <-
"Democrat and Partisan"
data$cell[data$version == 2 & data$partisantreatment == 2] <-
"Democrat and Non-Partisan"

# create controls

#affpol
data$affectivepolarization <- NA
data$inparty <- NA
data$outparty <- NA

data$inparty[which(data$pid=="Democrat")] <-
data$Q30_2[which(data$pid=="Democrat")]
data$inparty[which(data$pid=="Republican")] <-
data$Q31_2[which(data$pid=="Republican")]

data$outparty[which(data$pid=="Republican")] <-
data$Q30_2[which(data$pid=="Republican")]
data$outparty[which(data$pid=="Democrat")] <-
data$Q31_2[which(data$pid=="Democrat")]

data$affectivepolarization <- data$inparty -data$outparty

data$affectivepolarization <-
quantcut(data$affectivepolarization, q=3,
labels = c("Low", "Medium", "High"))


# Marlow-Crowne
```

```
data$Q20<-recode(as.character(data$Q20), "TRUE" = 1, "FALSE" = 0)
data$Q21<-recode(as.character(data$Q21), "TRUE" = 1, "FALSE" = 0)
data$Q22<-recode(as.character(data$Q22), "TRUE" = 1, "FALSE" = 0)
data$Q23<-recode(as.character(data$Q23), "TRUE" = 1, "FALSE" = 0)
data$Q24<-recode(as.character(data$Q24), "TRUE" = 1, "FALSE" = 0)
data$Q25<-recode(as.character(data$Q25), "TRUE" = 1, "FALSE" = 0)
data$Q26<-recode(as.character(data$Q26), "TRUE" = 1, "FALSE" = 0)
data$Q27<-recode(as.character(data$Q27), "TRUE" = 1, "FALSE" = 0)
data$Q28<-recode(as.character(data$Q28), "TRUE" = 1, "FALSE" = 0)
data$Q29<-recode(as.character(data$Q29), "TRUE" = 1, "FALSE" = 0)

data$marlowcrowne <- (data$Q20 + data$Q21 + data$Q22 +
data$Q23 + data$Q24 + data$Q25 + data$Q26 + data$Q27 + data$Q28 + data$Q29)/10

data$marlowcrowne <- quantcut(data$marlowcrowne, q=3, labels = c("Low",
"Medium", "High"))

# Short-Form Buss-Perry Aggression Questionnaire
data$Q63<-recode(data$Q63, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q64<-recode(data$Q64, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q65<-recode(data$Q65, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q66<-recode(data$Q66, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q67<-recode(data$Q67, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q68<-recode(data$Q68, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q69<-recode(data$Q69, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q70<-recode(data$Q70, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q71<-recode(data$Q71, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q72<-recode(data$Q72, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q73<-recode(data$Q73, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q75<-recode(data$Q65, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)

data$bussperry <- (data$Q63 + data$Q64 + data$Q65 + data$Q66 + data$Q67 +
data$Q68 + data$Q69 + data$Q70 + data$Q71 + data$Q72 + data$Q73 +
```

```
data$Q75)/12

data$bussperry <- quantcut(data$bussperry, q=3, labels = c("Low",
"Medium", "High"))

# Kalmoe-Mason
data$Q32<-recode(data$Q32, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)
data$Q33<-recode(data$Q33, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)
data$Q34<-recode(data$Q34, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)

data$Q35<-recode(data$Q35, "Yes" = 1, "No" = 0)
data$Q35<-recode(data$Q36, "Yes" = 1, "No" = 0)

data$Q77<-recode(data$Q77, "1 - Not at all" = 1, "2"=2, "3"=3,
"4"=4,"5 - A great deal" = 5)
names(data)
#political engagement index
data$Q16<-recode(data$Q16, "Yes" = 1, "No" = 0)
data$Q17<-recode(data$Q17, "Yes" = 1, "No" = 0)
data$Q18<-recode(data$Q18, "Yes" = 1, "No" = 0)

data$partscale <- (data$Q16 + data$Q17 + data$Q18)/3

data$partscale <- quantcut(data$partscale, q=3, labels = c("Low",
"Medium", "High"))
```

Note: We do not expect missing data because our Qualtics survey is set to "force response", but if there is missing data we will recode all missing data to its mean.

3 Study 1

3.1 Primary DVs

There are three primary variables of interest:

1. Do you support or oppose the actions of [Stan Gimm/Thomas Kelly]?
2. Was the driver justified or unjustified?
3. Should the driver face criminal charges?

```
# recode DVs

study1$supportactions <- NA
study1$supportactions[study1$partisantreatment==1] <-
study1$Q44[study1$partisantreatment==1]
study1$supportactions[study1$partisantreatment==2] <-
study1$Q50[study1$partisantreatment==2]
study1$supportactions <- recode(study1$supportactions,
"Strongly support" = 5, "Support"=4, "Neither support nor oppose"=3,
"Oppose"=2,"Strongly oppose" = 1)

study1$justified <- NA
study1$justified[study1$partisantreatment==1] <-
study1$Q45[study1$partisantreatment==1]
study1$justified[study1$partisantreatment==2] <-
study1$Q51[study1$partisantreatment==2]
study1$justified <-recode(study1$justified,
"Justified" = 1, "Unjustified" = 0)

study1$charged <- NA
study1$charged[study1$partisantreatment==1] <-
study1$Q46[study1$partisantreatment==1]
study1$charged[study1$partisantreatment==2] <-
study1$Q52[study1$partisantreatment==2]
study1$charged <-recode(study1$charged, "Yes" = 1, "No" = 0)
```

3.2 Factual Attention Check

We will ask each respondent to recall which state was mentioned in the treatment vignette.

```
# attention check
study1$passed <- 0
study1$passed[study1$Q43 == "Florida" & study1$partisantreatment==1] <- 1
study1$passed[study1$Q49 == "Oregon" & study1$partisantreatment==2] <- 1

table(study1$passed, study1$partisantreatment)
table(study1$passed)
```

3.3 Treatments

The design is a four cell design:

1. Democratic subject and partisan crime

2. Democratic subject and non-partisan crime
3. Republican subject and partisan crime
4. Republican subject and non-partisan crime

We will code the treatments as noted above.

3.4 Hypothesis tests

We expect support for violence to be low across all three dependent variables for all conditions. Specifically, we expect that tolerance for political violence will be no different from tolerance for non-political violence.

We will look for an effect in three different ways: by cell, by cell collapsing by party and between the partisan and non-partisan cells after collapsing by party. We will also look at the main results by attentiveness (those passing the factional attention check). Expecting support for violence to be larger for those who randomly click/don't pay attention.

```
# raw support (by condition)
table(study1$supportactions, study1$cell)
table(study1$supportactions, study1$cell)
table(study1$supportactions, study1$cell)

# raw support (pooled)
prop.table(table(study1$supportactions))
prop.table(table(study1$supportactions))
prop.table(table(study1$supportactions))

# Main results (general support)
summary(lm(supportactions ~ cell, data = study1))
summary(lm(justified ~ cell, data = study1))
summary(lm(charged ~ cell, data = study1))

# by attentiveness
summary(lm(supportactions ~ cell*passed, data = study1))
summary(lm(justified ~ cell*passed, data = study1))
summary(lm(charged ~ cell*passed, data = study1))

# Main results (general support by party)
summary(lm(supportactions ~ cell*pid, data = study1))
summary(lm(justified ~ cell*pid, data = study1))
summary(lm(charged ~ cell*pid, data = study1))

# Main results by in- and out-party
```

```
study1$alignment <- NA
study1$alignment[study1$version == 1 &
study1$partisantreatment == 1 & study1$pid == "Democrat"] <-
"Out-Party and Partisan"
study1$alignment[study1$version == 2 &
study1$partisantreatment == 1 & study1$pid == "Democrat"] <-
"Out-Party and Non-Partisan"
study1$alignment[study1$version == 1 &
study1$partisantreatment == 2 & study1$pid == "Democrat"] <-
"In-Party and Partisan"
study1$alignment[study1$version == 2 &
study1$partisantreatment == 2 & study1$pid == "Democrat"] <-
"In-Party and Non-Partisan"

study1$alignment[study1$version == 1 &
study1$partisantreatment == 1 & study1$pid == "Republican"] <-
"In-Party and Partisan"
study1$alignment[study1$version == 2 &
study1$partisantreatment == 1 & study1$pid == "Republican"] <-
"In-Party and Non-Partisan"
study1$alignment[study1$version == 1 &
study1$partisantreatment == 2 & study1$pid == "Republican"] <-
"Out-Party and Partisan"
study1$alignment[study1$version == 2 &
study1$partisantreatment == 2 & study1$pid == "Republican"] <-
"Out-Party and Non-Partisan"

study1$alignment <- as.factor(study1$alignment)

summary(lm(supportactions ~ alignment, data = study1))
summary(lm(justified ~ alignment, data = study1))
summary(lm(charged ~ alignment, data = study1))

# main result, comparing the two out-party treatments

t.test(study1$supportactions[study1$alignment ==
"Out-Party and Partisan"],
study1$supportactions[study1$alignment ==
"Out-Party and Non-Partisan"])
t.test(study1$justified[study1$alignment ==
"Out-Party and Partisan"],
```

```
study1$justified[study1$alignment ==
"Out-Party and Non-Partisan"])
t.test(study1$charged[study1$alignment ==
"Out-Party and Partisan"],
study1$charged[study1$alignment ==
"Out-Party and Non-Partisan"])
```

3.5 Heterogenous Treatment Effects

We have no clear predictions for heterogeneous treatment effects. However, we will explore whether our treatment varies by party

```
# Main results (general support by party)
summary(lm(supportactions ~ cell*pid, data = study1))
summary(lm(justified ~ cell*pid, data = study1))
summary(lm(charged ~ cell*pid, data = study1))
```

3.6 Robustness

The literature identifies several possible mechanisms that might prompt a person to support violence. Here we account for the most common: political engagement, affective polarization, social desirability (Marlow-Crowne Social Desirability Scale), and aggression (Buss-Perry Aggression Questionnaire. We also include six items from prior work that reportedly predict support for partisan violence: three measures of moral disengagement and three measures of prospective partisan violence(Kalmoe and Mason, forthcoming).

In all cases except for the Kalmoe-Mason items we create indexes by taking the mean of summed scale items. We then bin each variable into terciles. We will treat the Kalmoe-Mason items as separate predictors, though we may combine Q35 and Q36 into a single item coded to record attitudes toward the out-party.

The literature, based on correlational survey data, predicts that as affective polarization, political engagement and aggression increase so too does tolerance for political violence.

We also predict that social desirability will increase support for prospective political violence (Kalmoe-Mason), but not for support for actual political violence measured though our experiment. We suspect that this will be especially among strong partisans.

Finally, we predict that support for prospective violence poorly does not moderate support for violence in our experiments.

```
# Prospective violence and social desirability

summary(lm(Q77 ~ marlowcrowne, data = study1))
```

```
summary(lm(Q77 ~ marlowcrowne, data = study1[]))

#marlow-crowne
summary(lm(supportactions ~ alignment * marlowcrowne,
data = study1))
summary(lm(justified ~ alignment * marlowcrowne,
data = study1))
summary(lm(charged ~ alignment * marlowcrowne,
data = study1))

#buss-perry
summary(lm(supportactions ~ alignment * bussperry,
data = study1))
summary(lm(justified ~ alignment * bussperry,
data = study1))
summary(lm(charged ~ alignment * bussperry,
data = study1))

#political interest

summary(lm(supportactions ~ alignment * partscale,
data = study1))
summary(lm(justified ~ alignment * partscale,
data = study1))
summary(lm(charged ~ alignment * partscale,
data = study1))

#kalmoe mason

summary(lm(supportactions ~ alignment * Q32,
data = study1))
summary(lm(justified ~ alignment * Q32,
data = study1))
summary(lm(charged ~ alignment * Q32,
data = study1))

summary(lm(supportactions ~ alignment * Q33,
data = study1))
summary(lm(justified ~ alignment * Q33,
data = study1))
summary(lm(charged ~ alignment * Q33,
data = study1))
```

```
summary(lm(supportactions ~ alignment * Q34,
data = study1))
summary(lm(justified ~ alignment * Q34,
data = study1))
summary(lm(charged ~ alignment * Q34,
data = study1))

summary(lm(supportactions ~ alignment * Q35,
data = study1))
summary(lm(justified ~ alignment * Q35,
data = study1))
summary(lm(charged ~ alignment * Q35,
data = study1))

summary(lm(supportactions ~ alignment * Q36,
data = study1))
summary(lm(justified ~ alignment * Q36,
data = study1))
summary(lm(charged ~ alignment * Q36,
data = study1))

summary(lm(supportactions ~ alignment * Q77,
data = study1))
summary(lm(justified ~ alignment * Q77,
data = study1))
summary(lm(charged ~ alignment * Q77,
data = study1))

#affpol
summary(lm(supportactions ~ alignment * affectivepolarization,
data = study1))
summary(lm(justified ~ alignment * affectivepolarization,
data = study1))
summary(lm(charged ~ alignment * affectivepolarization,
data = study1))
```

4 Study 2

4.1 Primary DVs

There are three primary variables of interest:

1. The length of the recommended sentence.
2. Support for a possible pardon
3. Support for nullifying the conviction by imposing community service.

```
study2$nullify <- 0
study2$nullify[study2$Q53 == "Community service"] <- 1
study2$pardon <- recode(study2$Q76, "Strongly support" = 5, "Support"=4,
"Neither support nor oppose"=3, "Oppose"=2,"Strongly oppose" = 1)
```

4.2 Treatments

This is a six cell randomized design with six different partisan crimes.

```
$crime = array("vandalism",
"protesting without a permit",
"assault",
"arson",
"assault with a deadly weapon",
"murder"
);
```

4.3 Factual Attention Check

We will include an unrelated vignette on sea otter reintroduction. Following this vignette we will ask what state the story covers.

```
    # check for attentiveness
study1$passed <- 0
study2$passed[study1$Q82 == "Oregon"] <- 1
```

4.4 Hypothesis tests

We expect that support (with all measures) will decrease as the severity of the crime increases. We will also look at results by attentiveness, expecting that support for nullification is driven by random/inattentive responding.

```
# main results
table(study2$Q53, study2$item.crime)
#main result - pardon
summary(lm(pardon~item.crime, data=study2))
# main result - nullification
```

```
summary(lm(nullify~item.crime, data=study2))

# by attentiveness
# main results
table(study2$Q53, study2$item.crime, study2$passed)
#main result - pardon
summary(lm(pardon~item.crime*passed, data=study2))
# main result - nullification
summary(lm(nullify~item.crime*passed, data=study2))
```

4.5 Heterogeneous treatment effects

Again, we look at difference by PID with no predictions.

```
# by pid

# main results
table(study2$Q53, study2$item.crime, study2$pid)
#main result - pardon
summary(lm(pardon~item.crime*pid, data=study2))
# main result - nullification
summary(lm(nullify~item.crime*pid, data=study2))
```

4.6 Robustness

We use the same robustness measures from study 1

```
# robustness

#marlow-crowne
summary(lm(pardon ~ alignment * marlowcrowne, data = study2))
summary(lm(nullify ~ alignment * marlowcrowne, data = study2))

#buss-perry
summary(lm(pardon ~ alignment * bussperry, data = study2))
summary(lm(nullify ~ alignment * bussperry, data = study2))

#political interest

summary(lm(pardon ~ alignment * partscale, data = study2))
```

```
summary(lm(nullify ~ alignment * partscale, data = study2))

# kalmoe-mason

summary(lm(pardon ~ alignment * Q32, data = study2))
summary(lm(nullify ~ alignment * Q32, data = study2))

summary(lm(pardon ~ alignment * Q33, data = study2))
summary(lm(nullify ~ alignment * Q33, data = study2))

summary(lm(pardon ~ alignment * Q34, data = study2))
summary(lm(nullify ~ alignment * Q34, data = study2))

summary(lm(pardon ~ alignment * Q35, data = study2))
summary(lm(nullify ~ alignment * Q35, data = study2))

summary(lm(pardon ~ alignment * Q36, data = study2))
summary(lm(nullify ~ alignment * Q36, data = study2))

summary(lm(pardon ~ alignment * Q77, data = study2))
summary(lm(nullify ~ alignment * Q77, data = study2))

# affpol
summary(lm(pardon ~ alignment * affectivepolarization, data = study2))
summary(lm(nullify ~ alignment * affectivepolarization, data = study2))
```

References

Anderson, Michael L. 2008. "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American statistical Association* 103(484):1481–1495.

S11.2 PAP2 (Study 2 and Study 5

Pre-Analysis Plan: Support for Political Violence

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1 Preliminary Notes

- This is the pre-analysis plan for a survey experiment on support for political violence. There are two experiments in the survey.
- All of the code excerpted below is included in our upload to OSF along with our PAP. We excerpt it into the PAP to facilitate peer review.
- In the code that follows we use raw codings, though we may standardize for interpretability.
- We will conduct a multiple testing correction following Anderson (2008).

2 Data Cleaning

We will clean the data for the survey as follows:

```
library(tidyverse)
library(psy)
library(gtools)

data <- read_csv("data/data2.csv")

table(data$gc)
data <- data %>%
filter(gc==1)

#recode leaners
data$Q10[data$Q11 == "Democratic Party"] <- "Democrat"
data$Q10[data$Q11 == "Republican Party"] <- "Republican"
data$pid <- data$Q10
data$pid <- as.factor(data$pid)

# covariates
data$gender <- as.factor(data$Q4)
data$income <- as.factor(data$Q7)
data$education <- as.factor(data$Q8)
data$age <- data$Q14
data$race <- data$Q5

# strong partisans
data$Q12<-recode(data$Q12, "Strong Republican" = 1,
"Not a strong Republican" = 0)
data$Q13<-recode(data$Q13, "Strong Democrat" = 1,
"Not a strong Democrat" = 0)
```

```
data$strongpartisan <- 0
data$strongpartisan[data$pid=="Republican"] <- data$Q12[data$pid=="Republican"]
data$strongpartisan[data$pid=="Democrat"] <- data$Q13[data$pid=="Democrat"]

#recode experiments and conditions

data$experiment <- recode(data$experiment,
"1" = "Vignette (Rep)", "2" = "Expressiveness")

#study 1
data$cell <- NA
data$cell[data$version == 1] <- "Democrat Shooter"
data$cell[data$version == 2] <- "Republican Shooter"
data$cell[data$version == 3] <- "Shooter"

#study 2
data$study3cell <- NA
data$study3cell[data$payprompt == 1] <- "No Incentive"
data$study3cell[data$payprompt == 2] <- "Incentive"

# create controls

#affpol
data$affectivepolarization <- NA
data$inparty <- NA
data$outparty <- NA

data$inparty[which(data$pid=="Democrat")] <-
data$Q30_2[which(data$pid=="Democrat")]
data$inparty[which(data$pid=="Republican")] <-
data$Q31_2[which(data$pid=="Republican")]

data$outparty[which(data$pid=="Republican")] <-
data$Q30_2[which(data$pid=="Republican")]
data$outparty[which(data$pid=="Democrat")] <-
data$Q31_2[which(data$pid=="Democrat")]

data$affectivepolarization <- data$inparty -data$outparty

data$affectivepolarization <-
quantcut(data$affectivepolarization, q=3,
labels = c("Low", "Medium", "High"))


# Marlow-Crowne
```

```
data$Q20<-recode(as.character(data$Q20), "TRUE" = 1, "FALSE" = 0)
data$Q21<-recode(as.character(data$Q21), "TRUE" = 1, "FALSE" = 0)
data$Q22<-recode(as.character(data$Q22), "TRUE" = 1, "FALSE" = 0)
data$Q23<-recode(as.character(data$Q23), "TRUE" = 1, "FALSE" = 0)
data$Q24<-recode(as.character(data$Q24), "TRUE" = 1, "FALSE" = 0)
data$Q25<-recode(as.character(data$Q25), "TRUE" = 1, "FALSE" = 0)
data$Q26<-recode(as.character(data$Q26), "TRUE" = 1, "FALSE" = 0)
data$Q27<-recode(as.character(data$Q27), "TRUE" = 1, "FALSE" = 0)
data$Q28<-recode(as.character(data$Q28), "TRUE" = 1, "FALSE" = 0)
data$Q29<-recode(as.character(data$Q29), "TRUE" = 1, "FALSE" = 0)

data$marlowcrowne <- (data$Q20 + data$Q21 + data$Q22 +
data$Q23 + data$Q24 + data$Q25 + data$Q26 + data$Q27 + data$Q28 + data$Q29)/10

data$marlowcrowne <- quantcut(data$marlowcrowne, q=3, labels = c("Low",
"Medium", "High"))

# Short-Form Buss-Perry Aggression Questionnaire
data$Q63<-recode(data$Q63, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q64<-recode(data$Q64, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q65<-recode(data$Q65, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q66<-recode(data$Q66, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q67<-recode(data$Q67, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q68<-recode(data$Q68, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q69<-recode(data$Q69, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q70<-recode(data$Q70, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q71<-recode(data$Q71, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q72<-recode(data$Q72, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q73<-recode(data$Q73, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q75<-recode(data$Q65, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)

data$bussperry <- (data$Q63 + data$Q64 + data$Q65 + data$Q66 + data$Q67 +
data$Q68 + data$Q69 + data$Q70 + data$Q71 + data$Q72 + data$Q73 +
```

```
data$Q75)/12

data$bussperry <- quantcut(data$bussperry, q=3, labels = c("Low",
"Medium", "High"))

# Kalmoe-Mason
data$Q32<-recode(data$Q32, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)
data$Q33<-recode(data$Q33, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)
data$Q34<-recode(data$Q34, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)

data$Q35<-recode(data$Q35, "Yes" = 1, "No" = 0)
data$Q35<-recode(data$Q36, "Yes" = 1, "No" = 0)

data$Q77<-recode(data$Q77, "1 - Not at all" = 1, "2"=2, "3"=3,
"4"=4,"5 - A great deal" = 5)
names(data)
#political engagement index
data$Q16<-recode(data$Q16, "Yes" = 1, "No" = 0)
data$Q17<-recode(data$Q17, "Yes" = 1, "No" = 0)
data$Q18<-recode(data$Q18, "Yes" = 1, "No" = 0)

data$partscale <- (data$Q16 + data$Q17 + data$Q18)/3

data$partscale <- quantcut(data$partscale, q=3, labels = c("Low",
"Medium", "High"))
```

Note: We do not expect missing data because our Qualtics survey is set to “force response”, but if there is missing data we will recode all missing data to its mean.

3 Study 1 (Replication)

This is a replication of a prior study that was based on real events. Here we replicate with a contrived news story that is identical for both Democrats and Republicans. We also alter the context of the event to a shooting.

3.1 Primary DVs

There are three primary variables of interest:

1. Do you support or oppose the actions of Steven Wright?

2. Was the shooter justified or unjustified?
3. Should the shooter face criminal charges?

```
# recode DVs
study1$supportactions <- NA
study1$supportactions <- study1$Q44
study1$supportactions <- recode(study1$supportactions,
"Strongly support" = 5, "Support"=4,
"Neither support nor oppose"=3,
"Oppose"=2,"Strongly oppose" = 1)

study1$justified <- NA
study1$justified <- study1$Q45
study1$justified <-recode(study1$justified,
"Justified" = 1, "Unjustified" = 0)

study1$charged <- NA
study1$charged <- study1$Q46

study1$charged <-recode(study1$charged,
"Yes" = 1, "No" = 0)
```

3.2 Factual Attention Check

We will ask each respondent to recall which state was mentioned in the treatment vignette.

```
study1 <- data[data$experiment == "Vignette (Rep)",]

# attention check
study1$passed <- 0
study1$passed[study1$Q43 == "Iowa"] <- 1

table(study1$passed, study1$cell)
table(study1$passed)
```

3.3 Treatments

The design is a three cell design:

1. Democratic subject and partisan crime
2. Republican subject and partisan crime
3. Non-partisan crime

We will code the treatments as noted above.

3.4 Hypothesis tests

We expect support for violence to be low across all three dependent variables for all conditions. Specifically, we expect that tolerance for political violence will be no different from tolerance for non-political violence.

We will look for an effect in three different ways: by cell, by cell collapsing by party and between the partisan and non-partisan cells after collapsing by party. We will also look at the main results by attentiveness (those passing the factional attention check). Expecting support for violence to be larger for those who randomly click/don't pay attention.

```
# raw support (by condition)
round(prop.table(table(study1$supportactions,
study1$cell),1),2)
table(study1$justified, study1$cell)
table(study1$charged, study1$cell)

# raw support (pooled)
prop.table(table(study1$supportactions))
prop.table(table(study1$justified))
prop.table(table(study1$charged))

# Main results (general support)
summary(lm(supportactions ~ cell, data = study1))
summary(lm(justified ~ cell, data = study1))
summary(lm(charged ~ cell, data = study1))

# raw support (by condition) and attentiveness
round(prop.table(table(study1$supportactions,
study1$cell, study1$passed),1),2)
table(study1$justified, study1$cell, study1$passed)
table(study1$charged, study1$cell, study1$passed)

# by attentiveness
summary(lm(supportactions ~ cell*passed, data = study1))
summary(lm(justified ~ cell*passed, data = study1))
summary(lm(charged ~ cell*passed, data = study1))

# Main results (general support by party)
summary(lm(supportactions ~ cell*pid, data = study1))
summary(lm(justified ~ cell*pid, data = study1))
summary(lm(charged ~ cell*pid, data = study1))

# Main results by in- and out-party
```

```
study1$alignment <- NA
study1$alignment[study1$version == 1 &
study1$pid == "Democrat"] <- "In-Party and Partisan"
study1$alignment[study1$version == 2  &
study1$pid == "Democrat"] <- "Out-Party and Partisan"

study1$alignment[study1$version == 1 &
study1$pid == "Republican"] <- "Out-Party and Partisan"
study1$alignment[study1$version == 2 &
study1$pid == "Republican"] <- "In-Party and Partisan"

study1$alignment[study1$version == 3] <- "Non-Partisan"

study1$alignment <- as.factor(study1$alignment)

summary(lm(supportactions ~ alignment, data = study1))
summary(lm(justified ~ alignment, data = study1))
summary(lm(charged ~ alignment, data = study1))

# main result, comparing the out-party treatments to control

t.test(study1$supportactions[study1$alignment ==
"Out-Party and Partisan"], study1$supportactions[study1$alignment ==
"Non-Partisan"])

t.test(study1$justified[study1$alignment ==
"Out-Party and Partisan"],
study1$justified[study1$alignment == "Non-Partisan"])

t.test(study1$charged[study1$alignment == "Out-Party and Partisan"],
study1$charged[study1$alignment == "Non-Partisan"])

# main result, comparing the in-party treatments to control

t.test(study1$supportactions[study1$alignment == "In-Party and Partisan"],
study1$supportactions[study1$alignment == "Non-Partisan"])

t.test(study1$justified[study1$alignment == "In-Party and Partisan"],
study1$justified[study1$alignment == "Non-Partisan"])

t.test(study1$charged[study1$alignment == "In-Party and Partisan"],
```

```
study1$charged[study1$alignment == "Non-Partisan"])
```

3.5 Heterogenous Treatment Effects

We have no clear predictions for heterogeneous treatment effects. However, we will explore whether our treatment varies by party

3.6 Robustness

The literature identifies several possible mechanisms that might prompt a person to support violence. Here we account for the most common: political engagement, affective polarization, social desirability (Marlow-Crowne Social Desirability Scale), and aggression (Buss-Perry Aggression Questionnaire. We also include six items from prior work that reportedly predict support for partisan violence: three measures of moral disengagement and one measure of prospective partisan violence (Kalmoe and Mason, forthcoming).

In all cases except for the Kalmoe-Mason item we create indexes by taking the mean of summed scale items. We then bin each variable into terciles. We will treat the Kalmoe-Mason items as separate predictors, though we may combine Q35 and Q36 into a single item coded to record attitudes toward the out-party.

The literature, based on correlational survey data, predicts that as affective polarization, political engagement and aggression increase so too does tolerance for political violence.

We also predict that social desirability will increase support for prospective political violence (Kalmoe-Mason), but not for support for actual political violence measured though our experiment. We suspect that this will be especially among strong partisans.

Finally, we predict that support for prospective violence poorly does not moderate support for violence in our experiments.

```
# robustness

# Prospective violence and social desirability

summary(lm(Q77 ~ marlowcrowne, data = study1))

summary(lm(Q77 ~ marlowcrowne, data = study1[]))

#marlowe-crowne
summary(lm(supportactions ~ alignment * marlowcrowne,
data = study1))
summary(lm(justified ~ alignment * marlowcrowne,
data = study1))
summary(lm(charged ~ alignment * marlowcrowne,
data = study1))
```

```
#buss-perry
summary(lm(supportactions ~ alignment * bussperry,
data = study1))
summary(lm(justified ~ alignment * bussperry, data = study1))
summary(lm(charged ~ alignment * bussperry, data = study1))

#political interest

summary(lm(supportactions ~ alignment * partscale,
data = study1))
summary(lm(justified ~ alignment * partscale, data = study1))
summary(lm(charged ~ alignment * partscale, data = study1))

#kalmoe mason

summary(lm(supportactions ~ alignment * Q77, data = study1))
summary(lm(justified ~ alignment * Q77, data = study1))
summary(lm(charged ~ alignment * Q77, data = study1))

#affpol
summary(lm(supportactions ~ alignment * affectivepolarization,
data = study1))
summary(lm(justified ~ alignment * affectivepolarization,
data = study1))
summary(lm(charged ~ alignment * affectivepolarization,
data = study1))
```

4 Study 3

4.1 Primary DVs

1. Estimated Republican support for political violence.
2. Estimated Democratic support for political violence.

We will recode this variable in two ways. First, we will compute the distance of each response from the true population value. Second, we will pool in-party and out-party responses.

```
study3$repsupport <- study3$Q93_1
study3$demsupport <- study3$Q90_1

study3$inpartysupport <- NA
```

```
study3$outpartysupport <- NA

study3$inpartysupport[study3$pid == "Democrat"] <-
study3$demsupport[study3$pid == "Democrat"]
study3$outpartysupport[study3$pid == "Democrat"] <-
study3$repsupport[study3$pid == "Democrat"]

study3$inpartysupport[study3$pid == "Republican"] <-
study3$repsupport[study3$pid == "Republican"]
study3$outpartysupport[study3$pid == "Republican"] <-
study3$demsupport[study3$pid == "Republican"]

true_dem <- X
true_rep <- Y

#compute distance
study3$repdistance <- abs(study3$repsupport - true_rep)
study3$demdistance <- abs(study3$demsupport - true_dem)
```

4.2 Treatments

There are two experimental cells: one where we offer a cash incentive for correct responding and one where we offer no such incentive.

4.3 Factual Attention Check

We will include an unrelated vignette on sea otter reintroduction. Following this vignette we will ask what state the story covers.

```
    # check for attentiveness
study3$passed <- 0
study3$passed[study3$Q82 == "Oregon"] <- 1
```

4.4 Hypothesis tests

We expect that without incentives individuals will over-estimate group support for political violence. We further expect inattentiveness to increase support for partisan violence.

```
# main results
summary(lm(repdistance~study3cell, data=study3))
summary(lm(demdistance~study3cell, data=study3))

summary(lm(repsupport~study3cell, data=study3))
```

```
summary(lm(demsupport~study3cell, data=study3))

summary(lm(inpartysupport~study3cell, data=study3))
summary(lm(outpartysupport~study3cell, data=study3))


# by attentiveness
# main results
# main results
summary(lm(repdistance~study3cell*passed, data=study3))
summary(lm(demdistance~study3cell*passed, data=study3))

summary(lm(repsupport~study3cell*passed, data=study3))
summary(lm(demsupport~study3cell*passed, data=study3))

summary(lm(inpartysupport~study3cell*passed, data=study3))
summary(lm(outpartysupport~study3cell*passed, data=study3))
```

4.5 Heterogeneous treatment effects

Again, we look at difference by PID with no predictions.

```
# by pid

# main results
summary(lm(repdistance~study3cell*pid, data=study3))
summary(lm(demdistance~study3cell*pid, data=study3))

summary(lm(repsupport~study3cell*pid, data=study3))
summary(lm(demsupport~study3cell*pid, data=study3))
```

4.6 Robustness

We use the same robustness measures from study 1

```
# robustness

#marlow-crownesummary(lm(repdistance~study3cell,
data=study3))
summary(lm(demdistance~study3cell* marlowcrowne,
data=study3))
```

```
summary(lm(repsupport~study3cell* marlowcrowne,
data=study3))
summary(lm(demsupport~study3cell* marlowcrowne,
data=study3))

summary(lm(inpartysupport~study3cell* marlowcrowne,
data=study3))
summary(lm(outpartysupport~study3cell* marlowcrowne,
data=study3))


#buss-perry
summary(lm(repdistance~study3cell* bussperry, data=study3))
summary(lm(demdistance~study3cell* bussperry, data=study3))

summary(lm(repsupport~study3cell* bussperry, data=study3))
summary(lm(demsupport~study3cell* bussperry, data=study3))

summary(lm(inpartysupport~study3cell* bussperry, data=study3))
summary(lm(outpartysupport~study3cell* bussperry, data=study3))


#political interest
summary(lm(repdistance~study3cell* partscale, data=study3))
summary(lm(demdistance~study3cell* partscale, data=study3))

summary(lm(repsupport~study3cell* partscale, data=study3))
summary(lm(demsupport~study3cell* partscale, data=study3))

summary(lm(inpartysupport~study3cell* partscale, data=study3))
summary(lm(outpartysupport~study3cell* partscale, data=study3))

#kalmoe mason

summary(lm(repdistance~study3cell * Q77, data=study3))
summary(lm(demdistance~study3cell * Q77, data=study3))

summary(lm(repsupport~study3cell * Q77, data=study3))
summary(lm(demsupport~study3cell * Q77, data=study3))

summary(lm(inpartysupport~study3cell * Q77, data=study3))
```

```
summary(lm(outpartysupport~study3cell * Q77, data=study3))



#affpol
summary(lm(repdistance~study3cell* affectivepolarization,
data=study3))
summary(lm(demdistance~study3cell* affectivepolarization,
data=study3))

summary(lm(repsupport~study3cell* affectivepolarization,
data=study3))
summary(lm(demsupport~study3cell* affectivepolarization,
data=study3))

summary(lm(inpartysupport~study3cell* affectivepolarization,
data=study3))
summary(lm(outpartysupport~study3cell* affectivepolarization,
data=study3))
```

References

Anderson, Michael L. 2008. "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American statistical Association* 103(484):1481–1495.

S11.3 PAP3 (Study 3

Pre-Analysis Plan: Support for Political Violence - 3

Justin Grimmer   Clayton Nall   Matt Tyler   Sean J. Westwood

December 22, 2021

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1 Preliminary Notes

- This is the pre-analysis plan for a replication of a survey experiment on support for political violence.
- We use the treatment text from a prior study — "Study 1 (replication)" with some modifications.
- For this replication we remove the apolitical treatments.
- We removed all covariates except the general Kalmoe-Mason measure (with an updated response scale).
- We randomize a pre-treatment prompt to incentivize careful and thoughtful responding.

2 Data cleaning

This will proceed using the code from the last PAP with the alterations noted above.

3 Study 1 (Replication)

3.1 Primary DVs

There are three primary variables of interest:

1. Do you support or oppose the actions of Steven Wright?
2. Was the shooter justified or unjustified?
3. Should the shooter face criminal charges?

3.2 Factual Attention Check

We will ask each respondent to recall which state was mentioned in the treatment vignette. This is the same as the original study.

3.3 Treatments

The design is a four cell design:

1. Democratic suspect X Attention Incentivized
2. Republican suspect X Attention Incentivized
3. Democratic suspect X Attention Not Incentivized
4. Republican suspect X Attention Not Incentivized

3.4 Hypothesis tests

The primary analysis will compare distributions and means from the three different possible outcome scales by cell. We will group respondents and treatments into two groups ”in-group” and ”out-group”

The primary analysis will compare distributions and means from the three different possible outcome scales.

3.5 Heterogenous Treatment Effects

We have no clear predictions for heterogeneous treatment effects. However, we will explore whether our treatment varies by party, responses to a pre-treatment partisan cheerleading question (from Shafner and Luks 2018) and a pre-treatment survey trolling question (from the ANES).

S11.4 PAP3 (Study 2 Replication and Survey Addition

Pre-Analysis Plan: Support for Political Violence - 3

Justin Grimmer Clayton Nall Matt Tyler Sean J. Westwood

September 7, 2021

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4 Survey Questions **3**

4.1 Analysis . . . 4

1 Preliminary Notes

- This is the pre-analysis plan for a partial replication of a survey experiment on support for political violence.
- We use the treatment text from a prior study — "Study 1 (replication)" with some modifications.
- For this replication we remove the apolitical treatments and only provide in-party vignettes.
- We removed all covariates except for social desirability and the the general Kalmoe-Mason measure (with an updated response scale).
- We only measure justification. Additionally, we randomize the outcome question and scale between three options detailed below.

2 Data cleaning

This will proceed using the code from the last PAP with the alterations noted above.

3 Study 1 (Replication)

This is a replication of a prior study that was based on real events. Here we replicate with a contrived news story that is identical for both Democrats and Republicans. We also alter the context of the event to a shooting.

3.1 Primary DVs

There are is one primary variable of interest. We however, randomize the outcome scale and question stem:

1. Was the shooter justified or unjustified?
   Justified or Unjustified
2. How justified was the shooter?
   Not at all, a little, a moderate amount, a lot and a great deal
3. How justified was the shooter?
   Not at all, a little, a moderate amount, a lot, a great deal and don't know

3.2 Factual Attention Check

We will ask each respondent to recall which state was mentioned in the treatment vignette. This is the same as the original study.

3.3 Treatments

The design does not vary the treatment other than ensuring co-partisanship.

1. Democratic subject and partisan crime (always copartisan)

2. Republican subject and partisan crime (always copartisan)

3.4 Hypothesis tests

We expect that inattentive respondents will randomly respond when presented with a dicotemous outcome scale and will select a don't know when that option is available.

We expect support for violence to be low across all three versions of the question.

We expect support for violence to be larger for those who randomly click/don't pay attention.

The primary analysis will compare distributions and means from the three different possible outcome scales.

3.5 Heterogenous Treatment Effects

We have no clear predictions for heterogeneous treatment effects. However, we will explore whether our treatment varies by party.

3.6 Robustness

The literature identifies several possible mechanisms that might prompt a person to support violence. Here we account for the most common: political engagement, affective polarization, social desirability (Marlow-Crowne Social Desirability Scale), and aggression (Buss-Perry Aggression Questionnaire. We also include six items from prior work that reportedly predict support for partisan violence: three measures of moral disengagement and one measure of prospective partisan violence (Kalmoe and Mason, forthcoming).

In all cases except for the Kalmoe-Mason item we create indexes by taking the mean of summed scale items. We then bin each variable into terciles. We will treat the Kalmoe-Mason item as a separate predictors.

3.7 Robustness

We use the same robustness measures from study 1

4 Survey Questions

We also include two pre-treatment survey questions.

First, we replicate the original Kalmoe-Mason justification question with the original unbalanced scale:

“How much do you feel it is justified for $e://Field/p to use violence in advancing their political goals these days?”

- Not at all
- A little
- A moderate amount
- A lot
- A great deal

Next, we ask those who select any option other than “Not at all”:

“You reported that it is justified to use violence in advancing their political goals. What kind of violent crimes do think are justified?

Please be specific.”

This is an open-end question.

4.1 Analysis

This is exploratory analysis. We intend to analyze open-ended responses to identify patterns in what kinds of crimes respondents are thinking of. This will either be done by humans or via machine learning.

References

[1] Y Lelkes, SJ Westwood, The limits of partisan prejudice. *The Journal of Politics* **79**, 485–501 (2017).

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[3] GW Imbens, CF Manski, Confidence intervals for partially identified parameters. *Econometrica* **72**, 1845–1857 (2004).